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# HUMAN INTERACTIONS IN PHYSICAL AND VIRTUAL SPACES: A GIS-BASED TIME-GEOGRAPHIC EXPLORATORY APPROACH

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To the Graduate Council:

I am submitting herewith a dissertation written by Ling Yin entitled "HUMAN INTERACTIONS IN PHYSICAL AND VIRTUAL SPACES: A GIS-BASED TIME-GEOGRAPHIC EXPLORATORY APPROACH." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Geography.

Shih-Lung Shaw, Major Professor

We have read this dissertation and recommend its acceptance:

Bruce Ralston, Micheline van Riemsdijk, Lee Han

Accepted for the Council:
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Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)

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Accepted for the Council:

Carolyn R. Hodges
Vice Provost and Dean of the Graduate school

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# HUMAN INTERACTIONS IN PHYSICAL AND VIRTUAL SPACES: A GIS-BASED TIME-GEOGRAPHIC EXPLORATORY APPROACH

A Dissertation Presented for the
Doctor of Philosophy Degree
The University of Tennessee, Knoxville

Ling Yin

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# DELICATION

This dissertation is dedicated to my parents, Youcai Yin and Xiaolan Liu,

and my husband, Ye Tao

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# ABSTRACT

Information and communication technologies (ICT) such as cell phone and the Internet have extended opportunities of human activities and interactions from physical spaces to virtual spaces. The relaxed spatio-temporal constraints on individual activities may affect human activity-travel patterns, social networks, and many other aspects of society. A challenge for research of human activities in the ICT age is to develop analytical environments that can help visualize and explore individual activities in virtual spaces and their mutual impacts with physical activities.

This dissertation focuses on extending the time-geographic framework and developing a spatio-temporal exploratory environment in a space-time geographic information system (GIS) to facilitate research of human interactions in both physical and virtual spaces. In particular, this dissertation study addresses three research questions. First, it extends the time-geographic framework to assess the impacts of phone usage on potential face-to-face (F2F) meeting opportunities, as well as dynamic changes in potential F2F meeting opportunities over time. Secondly, this study extends the time-geographic framework to conceptualize and represent individual trajectories in an online social network space and to explore potential interaction opportunities among people in a virtual space. Thirdly, this study presents a spatio-temporal environment in a space-time GIS to facilitate exploration of the relationships between changes in physical proximity and changes in social closeness in a virtual space.

The major contributions of this dissertation include: (1) advancing the time-geographic framework in its ability of exploring processes of virtual communication alerting physical activity opportunities; (2) extending some concepts of the classical time geography from a physical space to a virtual space for representing and exploring virtual interaction patterns; (3) developing a space-time GIS that is useful for exploring patterns of individual activities and interactions in both physical and virtual spaces, as well as the interactions between these two spaces.

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# CHAPTER 1 INTRODUCTION

## 1.1 Research Background and Research Questions

A vast number of individual activities involve human interactions. People interact with family members at home; children go to school to learn from teachers; adults cooperate with colleagues in workplaces; during weekends, we hold parties, watch movies, go to shopping malls, and enjoy meals with friends, and in all of these situations we communicate with others. In order to satisfy the need for various human interactions, places dedicated to different functions emerged in the world, such as residence communities, business centers, shopping malls, schools, theatres, and so on. Engaging in activities and interactions across different places generates traffic. Concurrently, to alleviate spatial barriers across places, urban environments develop to compress different spatial functions to a limited spatial extent (Meier, 1962). Understanding spatio-temporal patterns and the processes of human interactions is crucial for research of human travel patterns and urban environments (Hanson, 1995; Miller and Shaw, 2001; Kwan, 2007).

The development of technologies has increased the modes of human interactions at a rapid pace that requires new approaches to studying the changes. Before the emergence of telecommunication, communicating instantaneously over space was difficult, and people conducted activities and interactions in *physical spaces*. For example, in order to purchase a book, an individual had to travel to a brick-and-mortar bookstore and pay a cashier; in order to chat with a friend, people had to arrange a face-to-face (F2F) meeting or write letters delivered through geographical space. This study refers to such human interactions mediated by physical presence as *physical interactions*. With innovations in the so-called information and communication technologies (ICT) such as landline and mobile phones, computers, and the Internet, *virtual spaces* has been created. We are able to conduct many activities in a virtual space that correspond to those in physical space with improved efficiency, such as instant chatting over distance, e-shopping, e-banking, distance education, and playing group online games. This study labels human interactions mediated by digital devices as *virtual interactions*.

Two types of linkages exist between the two spaces. ICT infrastructures present themselves as material existence (Figure 1.1). People depend on a physical *portal* (e.g., a telephone or a computer) to enter a virtual space. Information flows between the two spaces via portals. For instance, an individual sends an email to a friend via her computer and, after several hours, her friend reads this email via a mobile phone. Information generated in virtual space by one person is extracted from the virtual space by another person. The other link between the two spaces is about their influence on one another. The influences of ICT on individual activities and interactions are complex. Mokhtarian (1990) suggested that probably the most important ICT impact is that they are capable of relaxing constraints on physical activities and interactions. For example, people telecommute at home instead of traveling to workplaces, or instantly telecommunicate with friends instead of attending F2F meetings. The liberation of virtual interactions from the tyranny of physical space has produced debates on the possible demise of geographical distance in the ICT age (Cairncross, 1997). Are virtual interactions completely free of physical distance? Recent studies have indicated that the freedom of human interactions in virtual space is still affected by physical distance and time zone differences (Herbsleb *et al*., 2001; Liben-Nowell *et al*., 2005; Mok *et al*., 2009; Scellato *et al*., 2010). The corporeality of portals and people who use the portals to enter a virtual space links virtual interactions to the physical world.

With respect to human interactions, the emergence of virtual space raises several important research questions for geographers. For example, how do virtual activities affect physical interactions in space-and-time? Is there a geography of virtual space? Does physical proximity still affect virtual interactions? How can we analyze the relationships between physical distance and virtual interactions, and the communication time-lag caused by time zone differences? These research questions relate to one another and together provide a framework for understanding human interactions in the ICT age.

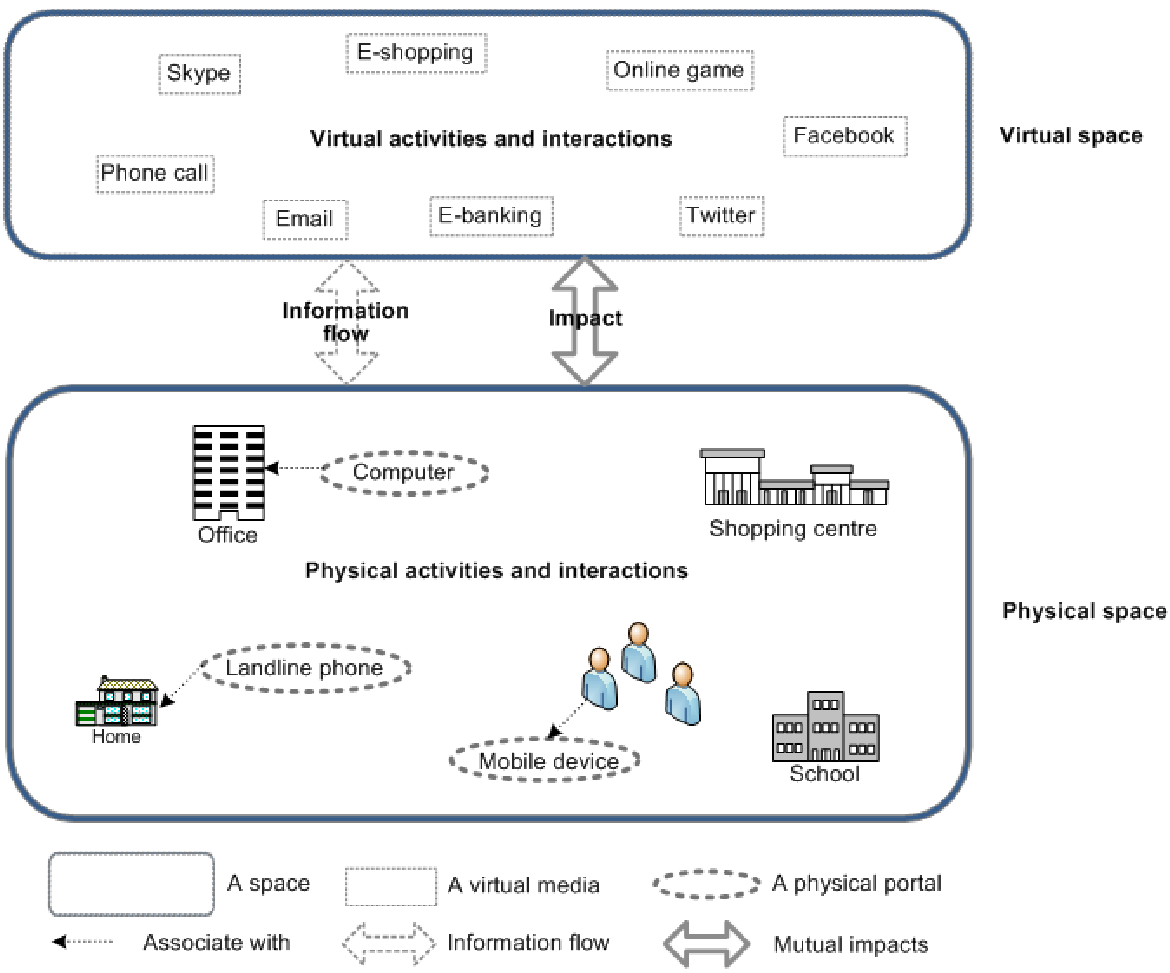



Figure 1.1 The relationships between physical space and virtual space

The use of ICT has blurred the traditional functions of places where people conduct activities and interactions. For instance, people with the Internet access can turn their homes or airport terminals into workplaces or purchase movie tickets via a cell phone while riding a train. Researchers therefore have suggested using people-based perspectives rather than traditional place-based perspectives to study human activity patterns in today's society (Miller, 2003; Kwan, 2007). Adams (2000) called individual-based approaches *micro-scale geography*, and Miller (2005b) emphasized the importance of such approaches as they provide individual-group linkages in study of human science. Moreover, collecting individual-based activity data (e.g., GPS tracking data, mobile phone tracking data, online communication data) has been made more feasible and affordable than before by today's technologies (Eagle and Pentland, 2005; González *et al*., 2008; Gidófalvi and Pedersen, 2009; Shaw and Yu, 2009; Scellato *et al*., 2010). Developing individual-based approaches to understanding human activities and interactions has thus gained increasing research attention.

Time geography, initially developed by Torsten Hägerstrand (1970), provides a useful framework for conceptualizing and representing human activities and interactions at the individual level in a space-time context. Its conceptual framework is rooted in linkages between the agency of individuals and the space-time structures of their lives (Cloke *et al*., 1991). It presents a *space-time path* for depicting an individual's physical trajectory over space and time, and a *space-time prism* for identifying the space-time possibilities of an individual's physical activities and interactions conditioned by external constraints (Hägerstrand, 1970; Lenntorp, 1976). As ICT have expanded individual activity opportunities from physical space to virtual space, recent studies have extended the classical time-geographic framework to handle virtual activities accordingly. Relevant studies discussed necessary space-time conditions for virtual interactions, visualized virtual interactions as extensions of physical space-time paths, and represented portal areas for entering virtual space (Kwan, 2000; Miller, 2005b; Yu and Shaw, 2008). Yet, a gap still exists between extended time-geographic frameworks and analytical frameworks that are able to support the aforementioned general types of research questions for understanding human activities and interactions in the ICT age. For instance, current time-geographic frameworks are not able to assess physical interaction opportunities affected by virtual communications or to reflect their dynamic changes over time. Current time-geographic frameworks still represent virtual activities and interactions based upon individual trajectories in a physical space. A time geography based on individual trajectories in a virtual space is needed to expand our recognition and understanding of virtual activities and interactions. For example, how can we represent an individual's trajectory in a virtual space? Furthermore, can we investigate the impact of physical proximity on virtual interactions by exploring the relationship between people's trajectories in physical and virtual spaces? Many challenges remain in the development of time-geographic frameworks.

In order to make a time-geographic analytical framework operational, researchers have made various efforts to implement time-geographic concepts in a geographic information system (GIS) to assist in human activity analysis (Miller, 1991; Kwan and Hong, 1998; Yu, 2006; Yu and Shaw, 2008; Shaw and Yu, 2009). These studies demonstrated the potential of GIS in representing and analyzing human activities within a three-dimensional spatio-temporal environment. These so-called space-time GIS allow recording physical activity-travel patterns in space and time. Compared with a classical statistical environment and a two-dimensional spatial analysis environment, a space-time GIS has a better capacity for tackling spatio-temporal data and revealing processes over space and time that hide behind aggregate patterns at discrete time moments (Shaw and Yu, 2009). However, it is still a challenge to design and implement a space-time GIS with exploratory functions able to assess the dynamic impact of ICT on physical interactions, visualize and explore virtual space and virtual interactions, and examine associations between physical movements and virtual interactions.

This study focuses on extending the time-geographic framework and developing a spatio-temporal exploratory environment in a space-time GIS to facilitate research of human interactions in physical and virtual spaces. It is designed under three sets of specific research questions:

1) How can a time-geographic framework be extended to assess potential F2F meeting opportunities between people under different phone access scenarios and to reflect dynamic changes of potential F2F meeting opportunities over time? How can this extended time-geographic framework be implemented in a space-time GIS? There are many possible ways ICT can influence individual activities and interactions. This study chooses the influence of various phone access scenarios on F2F meeting opportunities as an example to illustrate the feasibility of assessing the dynamic impacts of ICT use on individual interaction opportunities under a space-and-time context. Based upon various constraints (e.g., fixed workplace and time), the classical time-geographic framework is able to identify an individual's accessible places and available activity time at these places (Hägerstrand, 1970). The existing time-geographic framework explores potential synchronous presence opportunities among people (e.g., F2F meeting) by calculating their shared accessible places and shared available time windows (Miller, 2005b; Neutens *et al*., 2007; Yu and Shaw, 2008). Yet, previous studies did not consider how these shared space-time possibilities are

changed by virtual communication. In reality, virtual communication can facilitate a F2F meeting. For instance, people traveling with mobile phones can call friends near their current locations and have dinner together at a place. Without mobile phones, such F2F meeting opportunities are not available. This study seeks to articulate the process of phone communication influencing potential F2F meeting opportunities and incorporates the process into a time-geographic framework. Moreover, people's activity schedules change over time, especially with real-time updates enabled by ICT, such as phone calls or emails. By extending a time-geographic framework, Forer et al. (2007) discussed the dynamics of potential future activity opportunities with a changing schedule at a conceptual level. Developing an analytical and operational framework to reflect dynamic changes of potential F2F meeting opportunities over time remains a challenge. To incorporate the temporal component into GIS, Yu and Shaw (2008) developed a three-dimensional space-time GIS. Although this study develops spatio-temporal exploratory tools based upon a space-time GIS environment, designing analysis tools that are able to support the extended framework remains to be accomplished. For example, how can we let users assess dynamic F2F meeting opportunities under different phone access scenarios?

2) <u>How can the concepts, representations and analyses in a time-geographic framework for physical space and physical interactions be extended to represent and explore virtual space and virtual interactions? How can this extended time-geographic framework be implemented in a space-time GIS?</u> Batty (1997) claimed that a virtual space also has geography. There are few studies focused on developing an analytical framework with a spatio-temporal perspective to deal with virtual space and virtual

interactions. Classical time geography offers a useful framework to track individual trajectories and to explore potential interaction opportunities in a physical space. Is it possible to extend a time-geographic framework to track individual trajectories and to explore potential interaction opportunities in a virtual space? Many challenging questions are waiting to be tackled. For instance, since we call the virtual world "a space", are there virtual places in a virtual space? If so, how can we define and represent a virtual place? Is there a so-called "movement" for an individual across different virtual places? If so, are people's movements in a virtual space also limited by specific constraints? What are the constraints on people's movements in virtual space? How can we represent, visualize, and analyze people's movements and interactions in a virtual space? How can we define and represent virtual space-time paths and virtual space-time prisms? This study is presented as a starting point for development of a time-geographic framework suitable for studying activities and interactions in a virtual space. Meanwhile, there are challenges to implement these new concepts within a space-time GIS. For example, how can a space-time GIS represent a virtual space as well as patterns and processes in a virtual space?

3) <u>Which spatio-temporal exploratory approaches are able to examine associations between changes in physical proximity and changes in social closeness in a virtual space?</u> Physical proximity might increase the probability of strengthening interpersonal connections in a virtual space. For instance, some studies have suggested a positive relationship between geographical proximity and friendship probability in several popular online communities (Liben-Nowell *et al*., 2005; Scellato *et al*., 2010). Other studies also found a positive association between

> electronic contact frequency and geographical proximity (Mok *et al*., 2009). They examined the aggregate relationships between physical proximity and virtual interactions using classical statistical analysis. Nevertheless, few of these studies focused on interpersonal closeness changes in virtual space when physical proximity changes. For example, how do physical migrations affect people's social closeness in a virtual space? How can we analyze online communication and physical movement data to answer these questions? Specific spatio-temporal exploratory approaches are required in order to explore such spatio-temporal processes. In terms of implementing the proposed spatio-temporal exploratory approaches, is it feasible to implement them in a space-time GIS? If so, how can we integrate various analysis tools into a single space-time GIS environment? For example, how can we let users compare two people's physical movements and virtual interactions simultaneously in a space-time GIS?

As an effort of understanding human activities and interactions in the ICT age, this study addresses the above three research questions through the development of analytical frameworks and exploratory tools to facilitate studies of human interactions in physical and virtual spaces.

## 1.2 Organization of the Dissertation

This dissertation is organized into six chapters. The next chapter reviews relevant literature, including ICT and human activities, time geography, activity-based approaches, social network analysis, and space-time GIS. Based on the review of relevant literature, the section then identifies the specific efforts needed to answer the research questions discussed above. The next three chapters respectively focus on each of the three sets of research questions. Chapter 3 is devoted to extending the time-geographic framework in order to assess potential F2F meeting opportunities under different phone access scenarios and with a dynamic activity scheduling. Selected exploratory tools are developed and implemented in a space-time GIS. A hypothetical dataset is used to illustrate an example of using an analytical framework and a quantitative perspective to articulate how ICT affect individual activities in the physical world. Chapter 4 focuses on virtual interactions. The basic concepts in classical time geography are based upon physical space. These concepts include places, movements, activity constraints, individual trajectory, human interactions, space-time paths, and space-time prisms. This chapter discusses and redefines these concepts for a virtual space, particularly an online social network space. It then proposes and implements selected representations and analysis approaches in a space-time GIS. A sample of real communication records from social networking websites is used to demonstrate the representations and analysis approaches. Based on the representation and analysis of virtual interactions in Chapter 4, Chapter 5 develops an exploratory environment for assessing the associations between physical proximity changes and social closeness changes over time. This proposed spatio-temporal exploratory environment includes both classical statistical analysis and space-time GIS functions. With the virtual communication and physical migration data of a group of people, this chapter demonstrates the feasibility and effectiveness of integrating statistical and GIS environments to analyze the relationship between physical proximity and virtual interactions. Spatio-temporal exploratory tools are developed in the respective chapters for the proposed space-time GIS. Chapter 6 summarizes the major contributions of the study to time geography and space-time GIS, as well as its potential applications in studies related to transportation, urban study, social network analysis, social equity, and location-based services. This dissertation ends with discussions of future research directions.

# CHAPTER 2 LITERATURE REVIEW

This study focuses on developing analytical frameworks and an exploratory environment to facilitate research of human interactions in physical and virtual spaces from a spatio-temporal perspective. This chapter first reviews various relationships between human activities and ICT, followed by discussing studies concerning the three research questions of this study. Then it introduces three relevant methodologies: time-geographic framework, activity-based approach, and social network analysis. The basic analytical framework of this study is grounded in time geography. While summarizing classic and expanded time-geographic frameworks, this chapter identifies the challenges of further extending the time-geographic framework to address the research questions of this study. Activity-based approach in transportation research is then discussed due to its relationship with time geography. Another important approach to analyzing human interactions is social network analysis which represents interpersonal relationship as a network. This study incorporates social network analysis into the development of a time-geographic framework for virtual interactions. Thus, relevant techniques in social network analysis are introduced in this chapter. The last section of this chapter reviews efforts of developing space-time GISs that represents time and human activities as evolving processes in a space-time context.

## 2.1 ICT and Human Interactions

### *2.1.1 ICT and human activities*

ICT have been reported to influence human activity and interaction patterns in the physical world, which in turn may create effects on travel patterns, individual accessibility in urban environments, and social networks. The effects of ICT on individual travel activities have drawn extensive attention in geography and transportation research in the last two decades. The initial hypothesis of a relationship between ICT and travel focused on substitution or complementarity (Salomon, 1986). With increasing observations, Mokhtarian (2003) added two additional possible relationships of modification and neutrality. Therefore, there are four possible relationships between ICT and travel:

- *Substitution* relationship applies to telecommunication applications (e.g., telecommuting, e-shopping, and teleconferencing) that replace individual travel-based counterparts. Some researchers have conducted empirical studies of telecommuting, in which they have observed the substitution relationship. For example, Pendyala *et al*. (1991) and Koenig *et al*. (1996) both reported that telecommuters substantially reduced their trips and total distance traveled or vehicle-miles traveled. Similarly, Saxena and Mokhtarian (1997) found an increase in the amount of activities close to home that telecommuters performed on their telecommuting days.
- *Complementarity* relationship occurs when the use of one communication mode enhances or facilitates the use of other modes. Some studies suggest that telecommuting may lead to an increase in non-work trips and activities (Balepur *et al.*, 1998; Gould and Golob, 1997; Henderson and Mokhtarian, 1996). The study by Ferrell (2004) showed that home e-shopping tends to increase physical shopping trips. Farag *et al.* (2007) found that there is a positive relationship between online searching and the frequency of taking physical shopping trips.
- *Modification* relationship suggests that the use of one communication mode modifies the use of another mode. The most common examples are using cell phones to reschedule a

face-to-face meeting (F2F) in time and/or location, and using GPS to alter the route of a trip. Mokhtarian and Meenakshisundaram (1999) also implied that modification effects may be reclassifiable as one of the other three effects, depending on what the measure of interest is.

- *Neutrality* relationship refers to a situation in which the use of a particular communication mode has no effect on the use of other modes. For example, a phone call for casual chatting may have no impact on travel. Mokhtarian (2003) pointed out that the alternative to the telecommunication activity sometimes is not the travel-based activity, but rather not conducting the activity at all.

These four effects of ICT on individual travel are applicable to the effects of virtual interactions on physical interactions as well. For instance, telephone calls may cause any of the four effects on F2F meetings.

Besides the relationship between ICT and travel, Schwanen *et al.* (2008) identified three modalities of ICT effects on individual activities: *activity fragmentation*, *multi-tasking*, and *personalized networking*.

Couclelis (2000, 2004) proposed a hypothesis of *activity fragmentation*. In the ICT age, where and when a particular activity takes place does not link to a fixed answer. For example, before the ICT age, work usually meat a continuous activity at a fixed workplace from 9AM to 5PM. By contrast, in the ICT age, people can work on a flexible schedule, and/or at many possible places, such as home and Starbucks, where they can access the Internet or use telephones to communicate with their colleagues to perform their work duties. In other words, people can disintegrate an activity. Lenz and Nobis (2007) discussed why individuals "fragment" their activities and use cluster analysis to identify groups with different “fragmentation behavior”. Hubers et al. (2008) proposed three main dimensions to measure activity fragmentation: the number of fragments, the distribution of the sizes of fragments, and the temporal configuration.

ICT substantially enhance opportunities to *multi-task* by providing virtual activity opportunities. Kenyon and Lyons (2007) defined multi-tasking as the simultaneous conduct of two or more activities during a given time period. They also acknowledged that multi-tasking is likely to have important implications for the study of ICT effects on travel. Ohmori and Harata (2008) studied the multi-tasking phenomenon of train commuters in Tokoyo, and claimed that space-time accessibility measures such as activities while traveling will be important in future studies.

The *personalized network* is a product of ICT enabling a shift from territory-based households or groups to the individual who can create his/her own social network (Schwanen *et al*., 2008). Licoppe *et al*. (2008) used mobile phone based survey data to reconstruct urban mobilities and communication practice. Carrasco *et al*. (2008) explored the relationship between travel behavior, ICT use, and social networks, particularly from the perspective of social accessibility and agency. These studies present approaches that integrate sociodemographic information to explore ICT impacts on individual activities.

From the above literature, one should be able to see that a complex relationship exists between ICT and human activities. As Mokhtarian (1990, page 240) suggested, probably the most important ICT impact on human activities is that, “it permits much more flexibility in whether, when, where, and how to travel, and thus loosening the constraint of having to be at a certain place at a certain time.” Therefore, besides focusing only on one particular relationship, such as substitution or complementarity, it is also beneficial to study the relationships between

ICT and activity constraints. Kwan asked subjects to rank the fixity degree of activities in space and time to reveal the statistical pattern of individual activity constraints (Schwanen and Kwan, 2008). Meanwhile Schwanen interviewed subjects to understand how people use ICT to relax their activity constraints (Schwanen and Kwan, 2008). Unlike their empirical study to reveal the statistical patterns of relationships between ICT and human activities, the objective of this dissertation research is to develop an analytical framework to explore the potential effects of ICT on individual activity opportunities within a space-time context.

Due to the high complexity of ICT effects on individual activities, it is not realistic to develop a comprehensive analytical framework to support all situations. Therefore, as a starting point to explore these complex interactions, this study examines the ICT impact on potential physical interaction opportunities. Particularly, it investigates the influence of various phone access scenarios on F2F meeting opportunities.

### *2.1.2 Virtual communication and face-to-face communication*

Mokhtarian and Meenakshisundaram (1999) analyzed the inter-relationships among various modes of communication, including personal meetings, transfer of an information object (e.g., in-house documents, regular mail, and express or overnight mail), and electronic forms (e.g., phone, fax, and e-mail). The results show complementarity more often than substitution, but relationships specifically between electronic forms of communication and F2F meetings are not significant in either direction. Tillema *et al*. (2010) observed the generation effect between electronic and the F2F communication frequency. Another finding of their study is that the F2F communication frequency decreases with geographical distance between network members. The study by Boase et al. (2006) also has indicated that F2F contacts diminish with an increase in geographical distance between contact members.

The current findings suggest that virtual communications seem to enhance F2F meetings, which is likely due to the flexibility of scheduling F2F meetings using electronic communications. Furthermore, the relationship between F2F meeting frequency and geographical distance implies the spatial constraints for physical interactions. However, those studies ignored temporal constraints, such as the available time windows for meetings, as well as spatial context, such as the feasible meeting opportunities available to individuals. Therefore, this research will develop an analytical framework to explore the potential F2F meeting locations and time windows for individuals with different levels of phone access. This study will also offer researchers a better environment to understand the choice of a communication mode within a comprehensive geographical, sociodemographic, and activity schedule context.

### *2.1.3 Virtual space and virtual interactions*

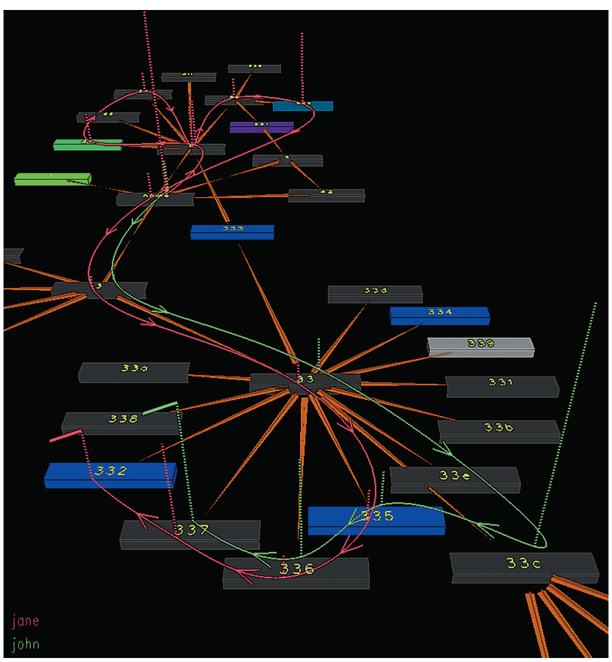
The second research question of this study focuses on virtual space. Geographers extract places to a space, and study patterns and processes in the space. When we call the world created by ICT a space, have we already implied there is geography in a virtual space? The term *cyberspace* was first used by the science fiction author William Gibson (Gibson, 1984). During 1990s, the Internet gradually became publicized, and a discussion about virtual space surged up in the geography community. Batty (1997) and Adams (1997) defined *cyberspace* as the use of computer networks to communicate. Batty (1997) referred to the study of virtual spaces and the ways virtual spaces changing physical spaces as *virtual geography*. Some geographers believed it brought in a new dimension to geography, and conceptualized the so-called *virtual geography*

(Batty, 1997; Gunkel and Gunkel, 1997; Giese, 1998; Kitchin, 1998; Crang *et al.*, 1999). This study considers virtual spaces as the global networks of information and communication technology infrastructures, including telephone networks and computer networks.

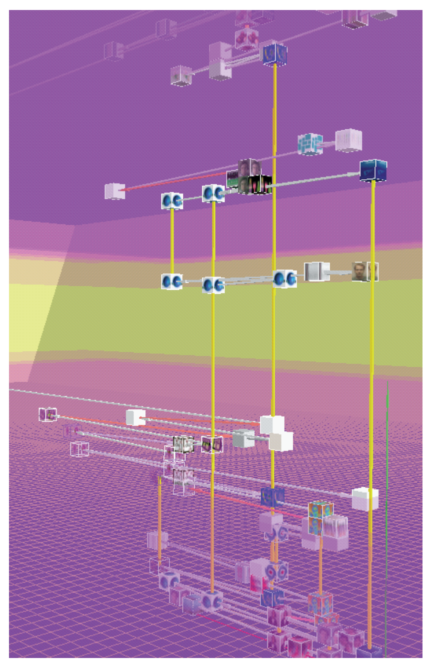
A map, as a fundamental representation of a space, can help understand patterns in a space. Researchers created a variety of virtual space maps, and Dodge and Kitchin (2001) edited an atlas of cyberspace. These creative maps covered ICT infrastructure distribution and telecommunication traffic flow based on geographical maps (Jiang and Ormeling, 1997; Cai *et al.*, 1999), topological connections of websites (Wills, 1997), an individual's path of visiting websites (Frécon and Smith, 1998; Cugini and Scholtz, 1999), communications and communities in virtual spaces (Adams, 2000), and maps of virtual reality environments (Taylor, 1997; Schroeder *et al.*, 2001).

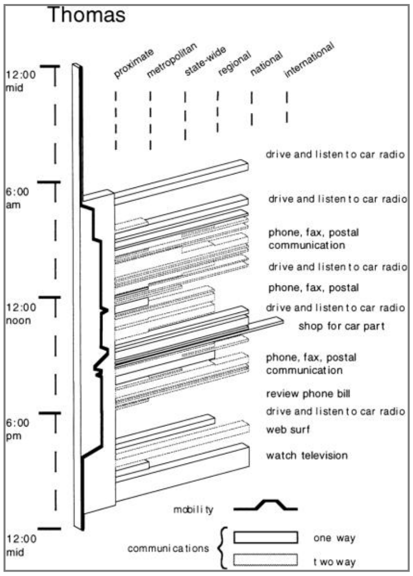
Some of these visualizations traced individual activities in virtual spaces. Cugini and Scholtz (1999) visualized the hierarchical structure of a website and the paths that users take through that site. In Figure 2.1a, two individual paths are shown, one green and one red. Frécon and Smith (1998) presented webpaths to link websites in the order of an individual's web browsing history. The x and y dimensions could be an abstract coordinate space or a real-world geography, and the vertical axis represents time (Figure 2.1b). Some visualization focused on human interactions. Adams (1995 and 2000) designed an extensibility diagram to represent the spatial scopes of an individual's communications by various ICT means, and also implemented it in a computer-aided design (CAD) application (Figure 2.1c). The vertical axis represents time through the day. The horizontal bars project out different communication activities, while the length of a horizontal bar shows the geographical scope of the communication. Through combining several individuals' extensibility diagrams, their interpersonal communications can be illustrated by the arcs linking them (Figure 2.1d).

Past research discussed virtual space and virtual interactions at the conceptual level, presented social network analysis for virtual communities, and also implemented visualization approaches for virtual activities and virtual interactions. Yet, these concepts, visualizations, and analysis functions are developed under different perspectives or different analytical frameworks. As a result, conceptual frameworks do not support visualizations, visualizations do not support analysis, and analysis functions are limited to existing theories or lack conceptual support. Such situations hindered our understanding of virtual space and virtual interactions. This dissertation study takes up the challenge to develop a single framework that is able to integrate concepts, visualizations, and analysis functions for virtual space and virtual interactions.

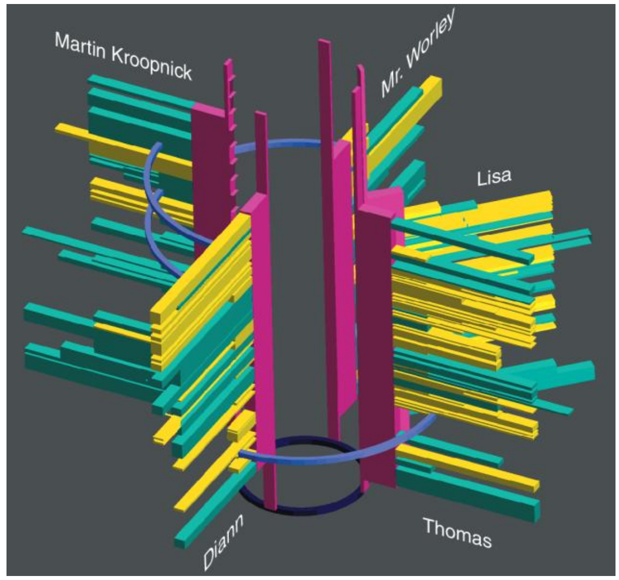


(a) Individual path of web browsing history (Cugini and Scholtz, 1999)


(b) Individual path of web browsing history (Frécon and Smith, 1998)




(c) An individual's communications (Adams, 2000)




(d) Communications between five individuals (Adams, 2000)

Figure 2.1 3D visualization of individual activities and interactions in virtual spaces

### *2.1.4 Spatio-temporal constraints on virtual interactions*

The third research question of this study is to investigate associations between physical distance and virtual interactions. "The shrinking map of the world" is a well-known chart by David Harvey (1989) (Figure 2.2). It uses four maps of the world in descending order of size to illustrate the change in the human experience of space and time with innovations in transport from 1500 through 1960s. This so-called *time-space compression* or *time-space convergence* becomes more apparent in the ICT era (Janelle, 1968 and 1973). Interpersonal communication largely depends on F2F meetings before the ICT age. Therefore, physical proximity between people was important to develop and maintain social connections during pre-ICT time (Hipp and Perrin, 2009). In other words, before the ICT age, people were likely to be closer with friends living in the same city than with friends living in other cities or other countries. With the aid of mobile phones, the Internet, and especially online social networking services (SNS) such as

Facebook and Twitter, people have extensive opportunities to discover friends and stay connected with them despite of their physical locations. Then does physical distance still affect people's social ties in the ICT age? In terms of developing and maintaining social networks, the conjecture that space is annihilated by ICT requires further examination.

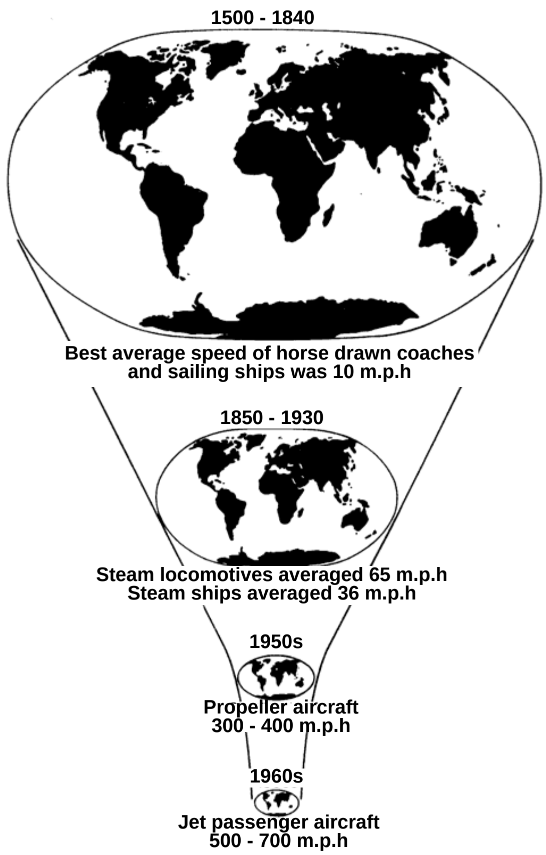



Figure 2.2 The shrinking map of the world (Harvey, 1989)

Liben-Nowell *et al*. (2005) constructed the social network on LiveJournal online community, and examined the relationship between friendship and geographical distance in the LiveJournal network. Their results showed that friendship probability declines over geographical distance in the online social community. Scellato *et al*. (2010) studied four large-scale online social networks, and found that clusters of friends are often geographically close. Their results also disclosed that purely location-based SNS such as BrightKite and FourSquare have more local ties, while information sharing SNS such as Twitter show more social connections on longer distances. Based on large-scale social networks in SNS spaces, the two studies validated the importance of geography in friendship development in the ICT age. Based upon self-reported data by participants, Mok *et al*. (2009) analyzed the effect of geographical distance on social closeness of people measured by the frequency of email/instance message and phone contact. The frequency of email/instant message and phone contact both drops over geographical distance within 500 miles, and then increases beyond 3000 miles. Their study proved the impact of geographical distance on maintaining and strengthening social ties with certain ICT means, but did not include communications in SNS spaces, which are becoming the key media of online communication. To the best of our knowledge, existing literature did not investigate the relationship between physical distance and social closeness in SNS spaces. The relevant studies of exploring social closeness changes with location changes over time from a spatio-temporal analysis perspective are also scarce. Classical statistical tools can be used to examine the aggregate relationships between physical proximity and virtual closeness. Investigating the dynamic relationships between physical proximity change and virtual closeness change over time remains a challenge.

One objective of this dissertation research thereby is to develop a spatio-temporal analytical framework for exploring the effect of physical proximity change on human interactions in a virtual space, particularly the relationships between physical proximity change and social closeness change in SNS spaces.

Time zone difference is another aspect of physical distance on the earth. It may bring in difficulties for synchronous telecommunication. In a SNS space, time zone difference might cause communication time-lag, which is an impact of temporal distance on virtual interaction. Some researchers studied the impact of time zone difference on global software development, and found that multi-sites development introduces delay of development speed compared with single-site development (Herbsleb *et al*., 2001). Espinosa *et al*. (2007) and Nguyen *et al*. (2008) suggested that such effect of time difference varied by different software development projects and collaborative environments. Ohira *et al*. (2010) extracted post time and reply time in the mailing list of selected open source software developers residing in two regions with six hours difference, and calculated the communication time-lag among developers in the same time zone and in different time zones. Their results did not show significant influence of time zone difference on communication time-lag. These studies focused on software development cooperation, and the communication involved was work-oriented. Few studies focused on communication time-lag in social networking websites among friends in different time zones. In this research, the case study from a SNS space will offer such an example. Moreover, this study will also develop a spatio-temporal approach to revealing the time zone influence on virtual communication at the individual level.

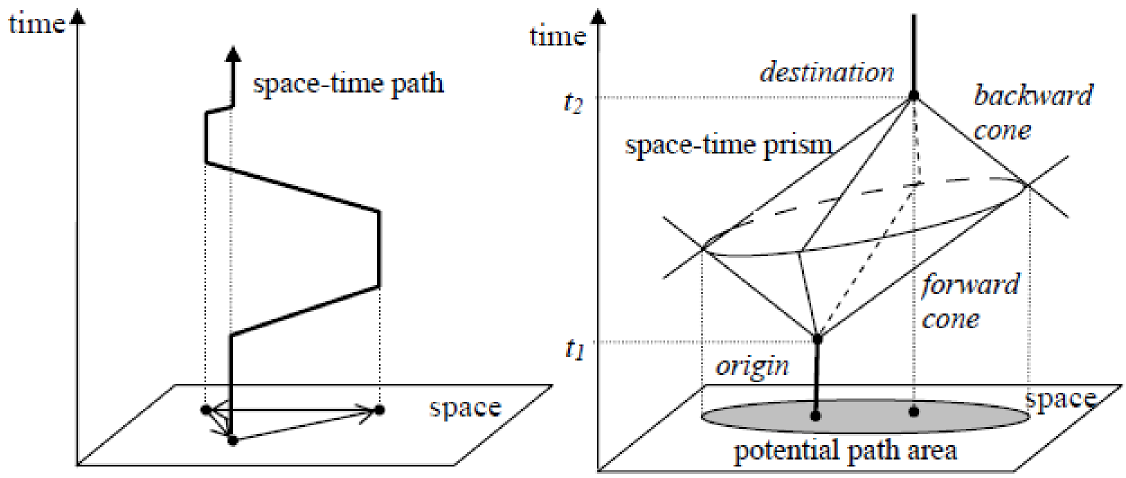
## 2.2 Time-geographic Framework for Human Interactions

Through examining the relationship of human activities and external constraints in a space-time context, classical time geography provides a basic framework to conceptualize, represent, and explore human activities and interactions (Hägerstrand, 1970). It has been suggested as a useful framework to support studies about ICT and human activities (Yu and Shaw, 2008; Shaw and Yu, 2009). This study therefore chose time geography as the basic research framework. This section will first review the classic time-geographic concepts related to this research. Then it will summarize different extended time-geographic frameworks for human interactions in both virtual and physical spaces, for uncertain activities, and for activity prediction. Meanwhile, it will identify and discuss the challenges for this research.

### *2.2.1 Classical time-geographic Framework*

Time geography, as initially developed by Torsten Hägerstrand (1970), provides a framework to both conceptualize and represent the interactions between the agency of individuals and the space-time structures of their lives (Cloke *et al.*, 1991). Hägerstrand (1970) identified three types of constraints for human activities and interactions. *Capability constraints* are physiological necessities (e.g., sleeping, eating) and available resources (e.g., auto ownership, cell phone ownership) that limit activity participation. *Coupling constraints* require an individual to occupy a certain location for some time in order to bundle with other individuals or entities for certain activities (e.g., person-to-person meeting, office hours). *Authority constraints* reflect general rules or laws that limit access to either spatial locations (e.g., military area) or time periods (e.g., store's open hours). This study employs the concept of capability constraints for the consideration of various phone access scenarios (e.g., landline phone access only, mobile phone access) and the concept of coupling constraints for physical interactions, particularly the F2F meeting opportunities discussed in Chapter 3. In addition, the time-geographic analytical framework presented in this study covers individual daily activity programs and access to telecommunications and transportation modes, which are subject to all three types of constraints suggested in time geography.

Due to the corporeality of human bodies, given a time moment, an individual can only physically present at one geographical place. The places an individual could be are conditioned by external constraints. The basic representation to connect an agency with its external constraints is a *space-time path* in a 3D coordinate system, which depicts an individual's trajectory over space and time (Figure 2.3a). In the 3D coordinate system, the *x* and *y* dimensions represent a geographical space, and the vertical dimension represents time. Individual-based movement tracking data supports generating space-time paths for individuals' historical movements in physical space (Kwan, 2000; Shaw *et al*., 2008; Yu and Shaw, 2008). Time geography also offers an analytical framework to explore potential activities conditioned by constraints. Individual activities are usually treated as *fixed* or *flexible* activities, based on their degree of flexibility in space and time. Although it is difficult to draw a distinct boundary between fixed and flexible activities, *fixed activities* are normally regarded as the activities that must be carried out at a fixed location and within a fixed time window, while *flexible activities* usually refer to the discretionary activities that can happen between two consecutive fixed activities (Miller, 1991; 2005a). A *space-time prism* identifies the space-time possibilities of a flexible activity between two pre-defined consecutive fixed activities (Hägerstrand, 1970; Lenntorp, 1976). For example, in Figure 2.3b, an individual cannot leave the origin place until *t1*, and has to arrive at the destination before *t2*. During the free time between *t1* and *t2,* the space-time prism, the enclosed 3D space by a forward cone and a backward cone, includes the potential opportunities the individual could be in space and time. The 2D projection of a space-time prism is a *potential path area*. With an individual's fixed activity schedule, we can use space-time paths to depict the location and time of fixed activities and use space-time prisms to identify the spatio-temporal extent of flexible activities.




(a) A space-time path (b) A space-time prism

Figure 2.3 Space-time path and space-time prism (Yu, 2005)

Moreover, the underlying ambition of time geography is to follow *processes* of individual activities (Lenntorp, 2004). The *project* concept thereby is proposed to depict a set of sequential activities in order to achieve a certain goal (Adams, 1995; Ellegård, 1999). Then the *project-event-activity* mode is used to organize activities involved within a process (Shaw and Yu, 2009).

### *2.2.2 Extended time-geographic framework for human interactions*

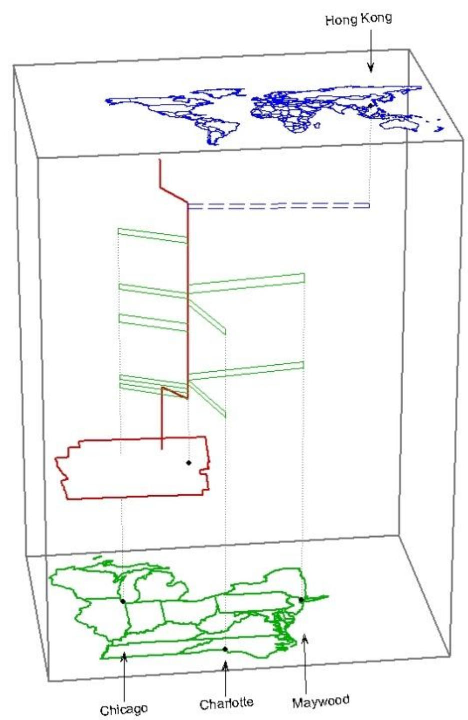
The classical time-geographic framework has been suggested as a useful analytical framework to study individual activities. However, ICT are changing individual activities. Realizing the limitations of the classical time-geographic framework to deal with virtual activities and interactions, researchers have been extending time-geographic frameworks to incorporate both physical and virtual activities.

With respect to human interactions, Janelle (1995, 2004) suggested four types of communication modes based on their spatial-temporal characteristics in physical space and virtual space: *Synchronous Presence* in physical space (i.e., having a F2F meeting), *Asynchronous Presence* in physical space (e.g., posting a message on a bulletin board), *Synchronous Tele-presence* in virtual space (e.g., having a telephone conversation or an online chat), and *Asynchronous Tele-presence* in virtual space (e.g., sending/reading an e-mail or a text message).

In physical space, given individual movement tracking data, synchronous presence among different individuals can be identified by the overlapping segments on their space-time paths (Yu, 2006; Kang and Scott, 2008; Yu and Shaw, 2008). If we only know the fixed activities of an individual, we can represent the potential activity pattern of this individual with a space-time path for his/her fixed activities and space-time prisms for his/her flexible activities that occur between the fixed activities. Miller (2005b) presented a rigorous measurement method to identify the potential synchronous presence space using interaction operations among space-time paths and space-time prisms. Neutens *et al*. (2007) implemented a time-geographic analysis framework to explore synchronous presence opportunities among multiple people. Neither of these studies considered the impacts of ICT communications on synchronous presence in physical space.

For the two communication modes in virtual space, Miller (2005b) also articulated necessary space-time conditions for potential synchronous/asynchronous tele-presence among people. When handling asynchronous tele-presence communications, it is necessary to specify a message sender and a message receiver. An asynchronous tele-presence communication is not completed until the message receiver has an opportunity to access the communication initiated by the message sender. Miller's measurement theory for time geography covers all four types of communication modes in both physical and virtual spaces (Miller, 2005b). The first part of this study (Chapter 3) extends Miller's work to analyze the potential synchronous presence opportunities due to the influence of synchronous or asynchronous tele-presence communications using telephones.

Some studies incorporated virtual activities and virtual interactions within the representation of time-geographical framework. Kwan (2000) and Yu (2005) represented virtual activities and virtual interactions as extensions of a space-time path based upon a physical space (Figure 2.4 and Figure 2.5). Yu (2005) also incorporated ICT access areas to represent the space-and-time people can enter a virtual space and conduct virtual activities (Figure 2.6). They however did not develop a conceptual framework to define and represent virtual space as a separated space, nor separately represented and analyzed virtual interactions. To better understand virtual interactions and their complex relationships with physical world, we need a framework that is able to systematically conceptualize, represent, and analyze virtual interactions. The second part of the study (Chapter 4) develops such a framework by migrating the classical time-geographic framework to a virtual space. It presents several new concepts, such as virtual space-time path and virtual space-time prism.




(Three scales of geographic spaces are included in the representation. The dark red path is an individual's space-time path within a geographical space, and the green and blue lines linked with the space-time path represent virtual interactions.)

Figure 2.4 A multi-scale, 3D representation of an individual's space-time paths (Kwan, 2000)

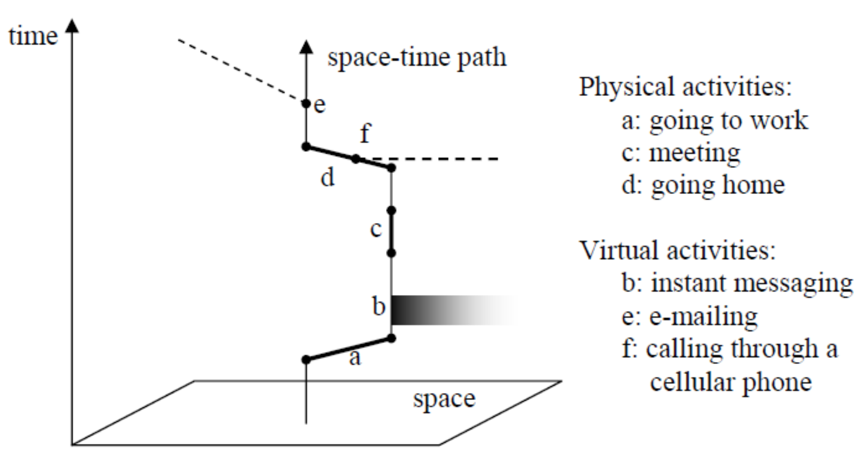



Figure 2.5 An extended space-time path with physical and virtual activities (Yu, 2005)

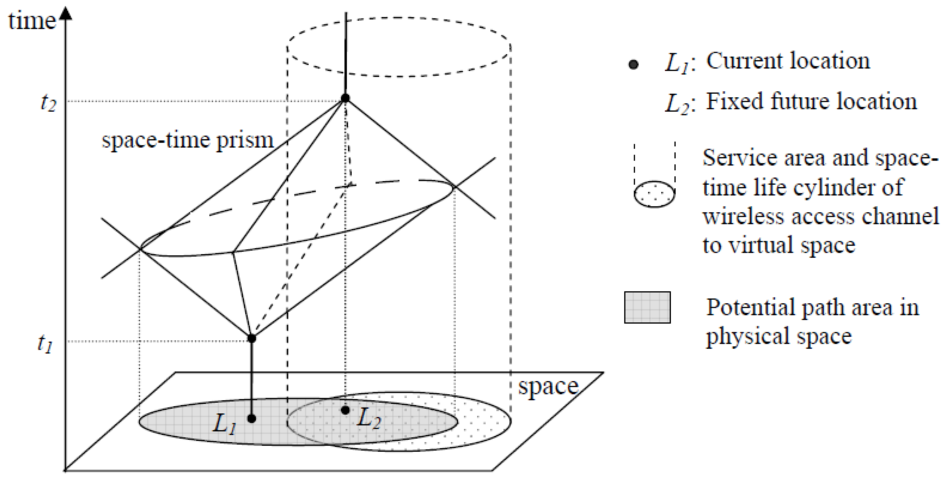



Figure 2.6 A space-time prism for virtual activities with wireless access channels (Yu, 2005)

### *2.2.3 Extended time-geographic framework for uncertainty in activities*

Treating individual activities as fixed activities and flexible activities has some limitations. First, the boundary between a fixed activity and a flexible activity is not unambiguous. In daily lives, people usually find activities in between fixed and flexible in space and time. Some researchers adopted several ways to depict the flexibility degree of an activity. Vilhelmson (1999) constructed a classification scheme of activities according to their flexibility in time and space, which was used to classify 135 stationary activities in the time-use survey. In this approach, the flexibility of activities can be vaguely represented by a scale. In the research of Schwanen *et al.* (2008) and Schwanen and Kwan (2008), the degree of temporal fixity and spatial fixity of an activity was respectively measured by a five-point scale, ranging from easy (1) to difficult (5), from which they investigated how variations in fixity levels are associated with various factors. Schwanen (2006; 2008) interviewed people about how they deal with the uncertainty of arrival time within coupling constraints, and suggested that time-spans of acceptable or appropriate arrival time might be identified in order to study the coupling constraints as well as the relaxation of ICT on coupling constraints. Neutens *et al*. (2007) presented the concept of *rough space-time prisms* to address three different types of uncertainty: spatial uncertainty of a fixed activity, temporal uncertainty of a fixed activity, and uncertain travel speed. Kuijpers *et al.* (2010) generalized the fixed location of a fixed activity to an *anchor region*, and created space-time prisms based on anchor regions instead of anchor points.

Second, people change their planned activities according to their dynamically changing schedules. Forer *et al.* (2007) pointed out the limitations of a dichotomy classification of activity while considering the effects of ICT on activity opportunities and activity scheduling. They presented a new concept, *assignation*, to replace the pre-defined fixed future activity that actually is, to some extent, flexible. Then they used a *dynamic prism* to represent the classical space-time prism. A dynamic prism is an evolving construct that can be part of a recursive and information-constrained process. As Figure 2.7 illustrates, the next assignation dynamically changes with real situations and the prism changes as well. Ohmori (2008) applied a time-geographic framework to show an example of dynamic rescheduling behavior by telecommunications (Figure 2.8). Yet, his example was only limited to representation, without developing an analytical framework.

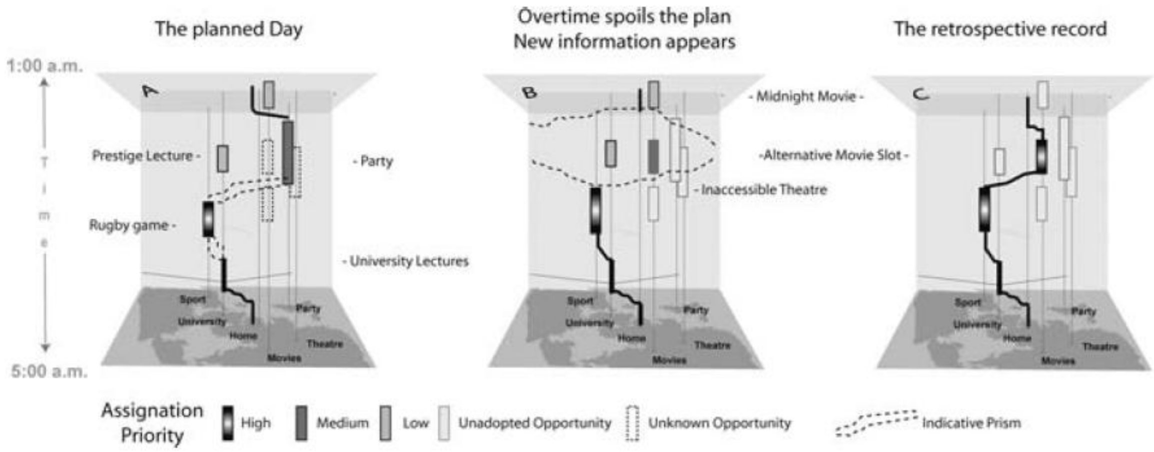



Figure 2.7 Activity opportunities, assignations, and prisms (Forer *et al.*, 2007)

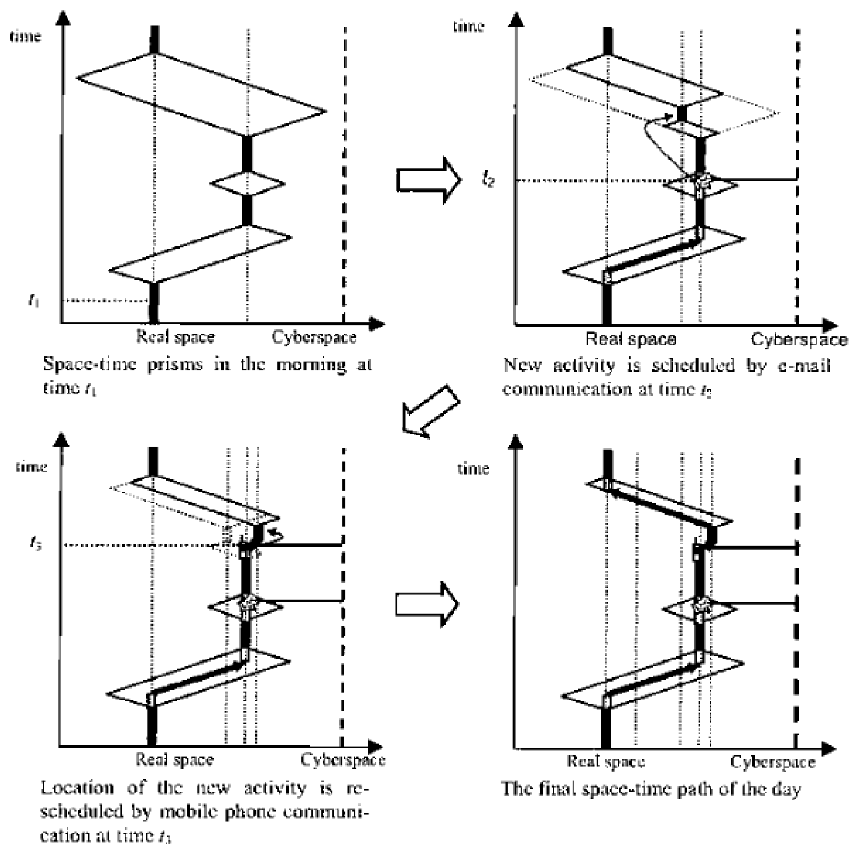



Figure 2.8 Dynamic change in a one-day activity schedule arranged by telecommunications (Ohmori, 2008)

This study follows the dichotomy classification of activity, but incorporates dynamic activity scheduling to reflect uncertainty of activities. Forer *et al.* (2007) proposed a useful framework with the same objective as the first part of this study: to develop an analytical framework for exploring to what extent ICT dynamically impact individual activities. Yet, their analytical framework is limited to a conceptual level, and has not been developed as an operational analytical framework. They did not consider the various effects of different ICT technologies and different activity purposes, nor did they explore the potential effects of ICT from the perspective of comparing the differences of activity opportunities when people have or do not have access to ICT.

### *2.2.4 Extended time-geographic framework for activity prediction*

The classical space-time prism approach identifies an individual's potential activity opportunities rather than predicting an individual's behavior. It offers the possibility of opportunities, not the probability of choosing a particular opportunity. Winter and Yin (2010) presented *probabilistic time geography*, which considers likelihoods for the locations of an individual at a particular time. Particularly they developed the mathematical foundations for modeling *probabilistic space-time prisms*. They claimed that the probability density within space-time prisms is non-uniform (Figure 2.9), and introduced a clipped bivariate normal distribution to formulate a space-time prism. Actually González *et al*. (2008) analyzed mobile phone tracking data from a large population, and found that human physical movements show a high degree of temporal and spatial regularity. Their study suggested the feasibility of developing probabilistic time geography through observing individuals' trajectories and summarizing movement patterns. This study does not have a large population's trajectories in physical space, but it collected online communication data from a group of people, thus, it develops a probabilistic virtual space-time prism in a virtual space (Chapter 4).

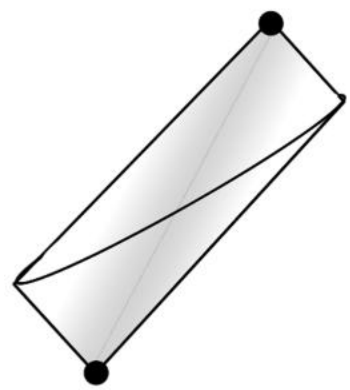


Figure 2.9 A probabilistic space-time prism

## 2.3 Activity-based Approach in the ICT Age

Travel theoretically is a derivative of the demand for activity participation (Hanson, 1995; Miller and Shaw, 2001). In other words, understanding individual travel requires a comprehension of individual activities. Individual activities also interact with urban form (Kwan, 2007; Ohmori, 2008). The distribution of function units in a built environment shapes individuals' activities in space and time. People will respond to the built environment and accordingly adjust their activity patterns. Massive spontaneous individual choices likely lead to mismatch between population demands and functional supply of urban areas. As a result, urban environment has to be rearranged to solve unbalanced distribution of function units and dwellers' needs. Individual activity studies, particularly on the spatio-temporal characteristics of individual activities, therefore can contribute to research on transportation and urban environment, such as travel demand analysis, individual accessibility, and urban planning. The underlying relationship between individual activities and spatial context impel to conduct this study.

Since the 1970s, activity-based approaches have received increasing attention in the transportation research community, and recent years in the urban studies community (Ohmori, 2008). Activity-based approaches study human activities in terms of activity locations, activity durations, travel modes, and activity scheduling, given the spatiotemporal environment of the potential activity opportunities, the state of the transportation network, and the relevant individual characteristics. Generally there are four different categories of activity-based models: constraints-based models, discrete choice models, rule-based models, and simulation models (Ettema and Timmermans, 1997; Timmermans, Arentze and Joh, 2002). Constraints-based models are based upon the activity-constraint framework of time geography. They explore possible activity opportunities and activity schedules under various constraints (Lenntorp, 1976; Jones *et al*., 1983; Dijst and Vidakovic, 1997). Discrete choice theory views choices as independent alternatives with a set of attributes that determine the utility of each alternative, and assumes individuals will choose the maximum utility alternative (Ben-Akiva and Lerman, 1985). Compared with constraints-based models that emphasize possible activity schedules, discrete choice models aim to predict the activity schedules' probability, which can provide more intuitive decision making assistance in travel demand modeling (Bowman, 1998; Bowman and Ben-Akiva, 2000; Bradley *et al*., 2010). Rule-based models do not make the assumption that everybody chooses the best alternative. They use sequential decision steps to simulate the activity planning and scheduling process (Recker *et al*., 1986; Gärling *et al*., 1989; Kwan, 1997; Kwan and Casas, 2006). Simulation models estimate individual activity patterns by simulating the individual reactions to the dynamic environment based on some simple rules (Kitamura *et al*., 2000). The recent development of activity-based models implicates that these different models are integrating one another, and are becoming more complicated in order to overcome their own limitations (Nagel and Rickert, 2001; Cetin *et al*., 2002; Arentze and Timmermans, 2007). In terms of activity-based approaches, the extended time-geographic framework for ICT impacts on physical interactions proposed in Chapter 3 basically belongs to constraints-based models. In addition, when dealing with dynamic activity scheduling, it also incorporates a certain decision-making rules, which make it capable of simulating a process of ICT altering activities.

This new generation approach of travel analysis can incorporate many missing travel characteristics in the traditional four-step approach, which is zone-based and trip-based (McNally, 1997; Davidson *et al.*, 2007). For instance, activity-based models are able to consider intra-household interactions, in-home activities, and activity scheduling, etc. (Scott and Kanaroglou, 2002; Gliebe and Koppelman, 2002 and 2005; Miller *et al*., 2005; Ruiz and Timmermans, 2006). They can also deal with the reaction of travelers to new transportation policies, and estimate the vehicle usage for individuals' travel, which would be useful for mobile source emission prediction.

Compared with the four-step models, which are aggregate approaches, and in which it is difficult to incorporate the effects of ICT, activity-based approaches study individuals' activities, and therefore potentially are able to incorporate the changing activities brought about by ICT. Although there are a vast amount of literature discussing potential impact of ICT on individual activities and interactions, most of them are limited to conceptual level or aggregate patterns observed from samples. Few of them formulated or modeled the process of virtual activities altering on physical activities and interactions. The first part of the research, which develops an analytical framework to explore the potential effects of phone communication on F2F opportunities with dynamic activity scheduling, can demonstrate an example to fill this gap.

## 2.4 Social Network Analysis for Human Interactions

As an intellectual tradition in social science, social network analysis applies graph theory to analyze interpersonal relationships among people. It is able to explore human interactions if the interpersonal relationship is measured by interaction degree. Visual analysis is an essential technique in social network analysis. The common visualization of social networks is a *social network graph*, which is an abstract representation of interpersonal relationship, not associated with geographical space (Scott, 2000). A social network graph therefore is applicable for human interactions in both physical and virtual spaces. For example, an online social network or a mobile phone network can be represented by a social network graph (Garton *et al.*, 1997; Catanese and Fiumara, 2010). Because of its capability of representing virtual interactions, this study incorporates it into the time-geographic framework for virtual space and virtual interactions in Chapter 4. The following two sections introduce static social network graph for an aggregated pattern of a time period and dynamic social network analysis for an evolving pattern over a time period.

### *2.4.1 Static social network graph*

Static social network graph has been studied for decades in sociology (Scott, 2000). In terms of distance measure between people, there are two types of social network graph: one is based upon *topological distance* of graph theory, and the other is based upon *Euclidean distance*.

*Graph theory* uses *vertices* to represent objects and *edges* to represent relations between objects. The distance between two vertices is measured by the number of edges in the shortest path that connects them, which is so-called *topological distance*. For example, if person A and person C both are friends of person B, but person A does not know person C, the adjacency matrix for the three persons' friendship connection is shown in

Table 2.1a, and the social network graph is shown in Figure 2.10a. According to the number of edges connecting objects, the topological distance between person A and person C is two edges (

Table 2.1b). In a topological distance-based social network graph, the length of an edge does not have a meaning. The relative locations of objects do not have meanings either. In other words, there are infinite ways to draw Figure 2.10a, as long as point A and point C are connected with point B, such as Figure 2.10c.

Table 2.1 An adjacency matrix and its topological distance matrix

| | A | B | C |
|---|---|---|---|
| A | — | 1 | 0 |
| B | 1 | — | 1 |
| C | 0 | 1 | — |

(1 means they are friends, 0 means they are not friends, — means not applicable)

(a) The adjacency matrix of person A, B, and C

| | A | B | C |
|---|---|---|---|
| A | 0 | 1 | 2 |
| B | 1 | 0 | 1 |
| C | 2 | 1 | 0 |

(b) The topological distance matrix among person A, B, and C

Table 2.2 A distance matrix

| | A | B | C |
|---|---|---|---|
| A | 0 | 1 | 3 |
| B | 1 | 0 | 2 |
| C | 3 | 2 | 0 |

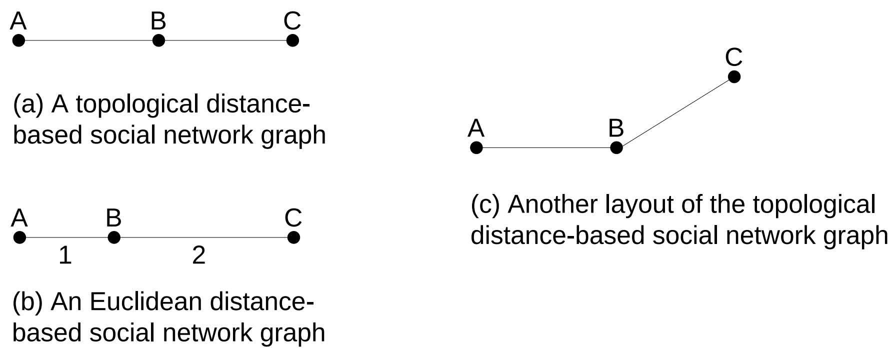



Figure 2.10 Two types of social network graph

A social network layout based on graph theory can illustrate connections among people, but cannot show the "closeness" or distance between people rigorously. For example, person B is closer to person A than to person C. The social distance index between person B and person A is one unit, while the social distance index between person B and person C is two units. Figure 2.10b reflects such closeness and distance information by *Euclidean distance*, which is the length of the straight line connecting two points. In Figure 2.10b, the Euclidean distance between point B and point C is twice as far as the Euclidean distance between point B and point A. Moreover, in a topological distance-based graph such as Figure 2.10a, no matter where point A or point C locates, the topological distance between them is always two edges. In a Euclidean distance-based graph, however, the Euclidean distance between point A and point C is determined by the locations of point A and point C. For example, in Figure 2.10b, the Euclidean distance between point A and point C is three units. If point A or point C moves, the Euclidean distance between them will change. Similarly, given the distance matrix shown in Table 2.2, Figure 2.10b shows the only layout that correctly maps the distances among them.

In practice, creating a Euclidean distance-based social network graph by a given distance matrix is not as straightforward as it is shown in Figure 2.10b. The data usually is high dimensional (e.g., more than four objects), and not all such problems have an exact solution. For example, if we have a "closeness" matrix of 20 people, and need a more intuitive representation to understand their complicated relationships, there is probably no way in mathematics that can create a low dimensional layout of the 20 people (e.g., 2D or 3D) that can 100% satisfy the given distance matrix.

*Multidimensional scaling* (MDS) is a useful mathematical tool that enables us to represent similarities (e.g., "closeness" between people) or dissimilarities (distance) of objects spatially in a map (Schiffman *et al*., 1981). The input of MDS is a $n \times n$ distance matrix of $n$ objects, and the output of MDS is a $n \times m$ matrix, which consists of $n$ vectors of coordinates. The $i$th vector $(x_{i1}, x_{i2}, \ldots x_{im})$ in the output matrix is the object $i$'s coordinates in a Euclidean $m$-space. Although a higher dimensional solution generally gives a better fit to the data, we would like $m$ to be a low dimension such as two dimensions or three dimensions, which can be simply visualized for interpretation.

Computer-based MDS procedures seek a configuration in a given dimensionality whose distances satisfy the input distance matrix as closely as possible (Borg and Groenen, 2005). The condition "as closely as" is quantified by a *loss function*. The loss function is a mathematical expression that represents the overall differences between the distances of objects in the output configuration and the distances of objects in the input distance matrix. Like solving optimization problems, MDS procedures start from an initial layout, and keep altering it and searching a better layout that has a less value of the loss function. When the loss function achieves convergence, MDS procedures will stop searching with the last solution.

When using MDS to map people's places in a 2D space, a distance measurement or a "closeness" measurement has to be defined first to generate the distance matrix. For instance, in a social network website such as Facebook, the "closeness" between two persons could be measured by the count of messages to each other, the average response time to the other's posts, the response rate to the other's posts, or the intimacy degree of their communication contents if data permits and research requires (Feldman and Sanger, 2007). The distance between two persons can be a certain mathematical transformation of their "closeness" measurement. For example, if we use the total message count $n$ between two people as the "closeness" measurement, $1/n$ can be a distance measurement.

### *2.4.2 Dynamic social network representation*

The social network structure among people is evolving over time. We are not only interested in an aggregate pattern for a particular time period, but also interested in the dynamic changing pattern across different time periods. The most straightforward approach is to animate snapshots of social network graphs in temporal sequence (Leydesdorff *et al.*, 2008). Yet, it is a challenge for observers to remember and compare different patterns in different snapshots. Another common approach is to trace an individual's subgroup identity with a subgroup-time graph (Kang *et al.*, 2007). It is easier to observe the evolution of an individual's subgroup membership over time, but it gives up the social network graph representation and therefore is not able to illustrate an individual's position within the entire group. There is some other work in dynamic social network representation, but there are scarce attempts to combine dynamic social network representation and spatio-temporal analytical frameworks (Branke, 2001; Brandes, 2003; Gaertler and Wagner, 2006; Yang *et al.*, 2008). Reda (2009) first used space-time paths to represent dynamic social networks. He created a space-time path for each geographically-bounded subgroup in the entire social network to represent their movements in a geographical space. His approach is limited to geographically-bounded social interactions, and the meaning of space-time paths in his visualization still stays in the physical world. To explore virtual interactions from a spatio-temporal analysis perspective, this study has a challenge to extend the meaning of space-time paths from geographical space to virtual space.

## 2.5 Space-time GIS for Human Interactions

Geographic information systems (GIS) are becoming essential environments for spatial analysis in many fields. However, it is challenging to represent and analyze human activities in GIS because of their dynamic spatio-temporal characteristics. Attempts have been made to implement time-geographic concepts in GIS to assist in human activity analysis. Miller (1991) first implemented the space-time prism concept in a GIS environment and calculated the network-based potential path area for the study of individual accessibility. Along with the work of Miller (1991), several more studies have been made to use GIS to measure space-time constrained individual accessibility and to identify available opportunities (Kwan and Hong, 1998; Miller, 1999; Miller and Wu, 2000; Weber and Kwan, 2002; Kim and Kwan, 2003; Weber, 2003). These studies offered procedures in GIS to delimit the extent in a road network that is physically accessible to an individual under certain constraints in space and time based on two-dimensional GIS design and representation. Yu (2005) developed a three-dimensional representation of a space-time prism in GIS (Figure 2.11). Another important time-geographic concept, the space-time path, has also been tackled with GIS representations. Kwan (2000b) and Kwan and Lee (2003) visualized space-time paths in a three-dimensional GIS environment to assist in the exploration of spatio-temporal patterns of human activities. Using a multi-scale representation in GIS, Kwan (2000a) offered a conceptual model to represent the extensibility of a human agent, showing connections through virtual space as links stretched out from space-time paths (Figure 2.4). Using computer-aided design (CAD) diagrams, Adams (1995, 2000) also represented human activities with a space-time path approach (Figure 2.1c and d). Yu (2006) used dynamic segmentation and linear referencing to implement space-time paths that can effectively represent physical activities as well as virtual activities. The work of Yu and Shaw (2008) also included some analysis functions, such as activity queries by time and location, relationship analysis between space-time paths and space-time prisms. In their later work, Shaw and Yu's (2009) *project* concept was used to organize related activities as spatio-temporal processes. Shaw *et al*. (2008) also implemented a concept of *generalized space-time path* in a space-time GIS to represent physical movement trend of a group people with similar physical movement patterns. As an alternative GIS data representation, Miller and Bridwell (2009) applied continuous fields to formulate analytical definitions of the space-time path and prism for cases where unobserved components are characterized by minimum cost curves through an inverse velocity field rather than straight line segments through a uniform velocity plane.

The above studies demonstrate the potential of GIS to represent and analyze human activities and interactions with a spatio-temporal scope. This study needs a space-time GIS that can support exploring the dynamic effects of phone communication on physical interaction opportunities, representing and exploring spatio-temporal patterns of virtual interactions in a virtual space, and examining associations between physical distance change and virtual interactions. Designing and implementing a space-time GIS to meet such needs is still a challenge.

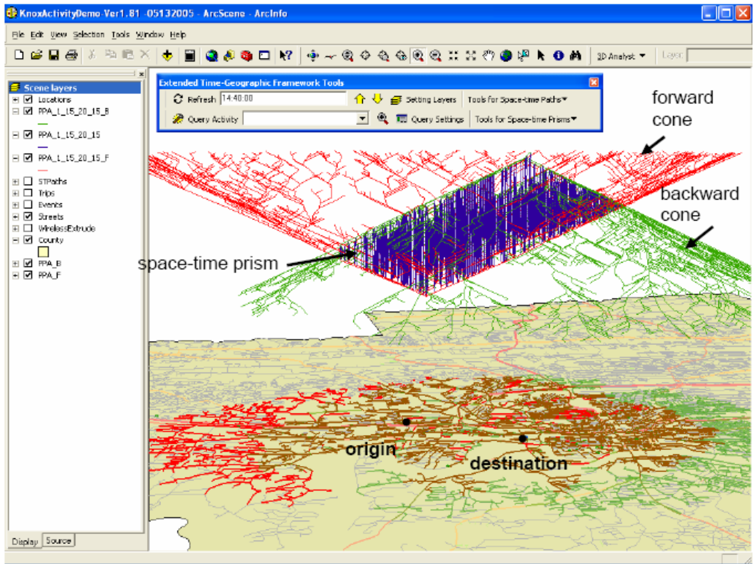



Figure 2.11 A 3D space-time prism based on street network in ArcScene (Yu, 2005)

## 2.6 Research Design

The underlying goal of this study is to develop analytical frameworks and an exploratory environment to facilitate research of human interactions in physical and virtual spaces from a spatio-temporal perspective. The three main research questions include assessing the impact of phone communication on F2F meeting opportunities, representing and exploring virtual interactions, and investigating the impact of physical distance on virtual interactions. Figure 2.12 shows the research design of this study. Chapters 3, 4, and 5 respectively tackle each of the three research questions. Focusing on the dynamic process of phone communication affecting F2F meeting opportunities, Chapter 3 extends the time-geographic framework in conceptual and analytical levels. Chapter 4 extends the time-geographic framework to a virtual space from a conceptual level to analytical approaches. It also incorporates representation of social network analysis to tackle abstract virtual space and virtual interactions. Based on the extended time-geographic framework in Chapter 4, Chapter 5 develops spatio-temporal exploratory approaches to facilitate scrutinizing associations between changes in physical distance and virtual interactions. Each chapter also designs exploratory tools and implements them in a space-time GIS. As a whole, the space-time GIS offers a spatio-temporal exploratory environment. With the exploratory environment, researchers can better understand human interactions in the ICT age.

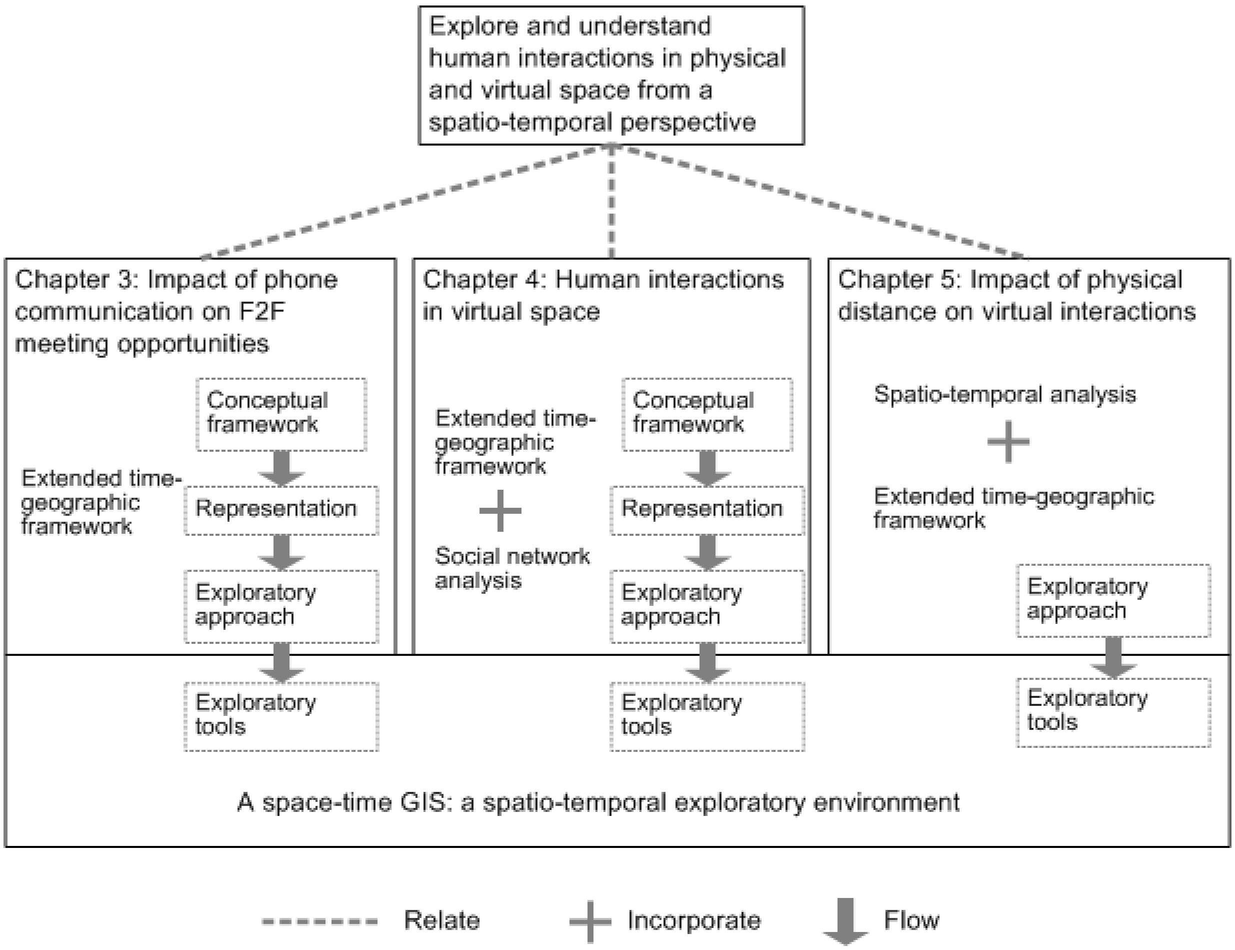



Figure 2.12 Research design of this study

# CHAPTER 3 IMPACT OF PHONE COMMUNICATION ON F2F MEETING OPPORTUNITIES

People can use virtual interactions enabled by ICT to replace physical interactions such as F2F meetings. They can also arrange and rearrange F2F meetings based on their changing activity schedules. Some studies suggest that ICT could enhance F2F meeting opportunities and increase the flexibility of scheduling F2F meetings (Mokhtarian and Meenakshisundaram, 1999; Eagle and Pentland, 2005; Tillema *et al*., 2010). However, limited progress has been made on assessing the impact of ICT on F2F meeting opportunities (Schwanen and Kwan, 2008).

This chapter focuses on the influence of various phone accesses on potential F2F meeting opportunities under dynamic activity scheduling. It offers an example to illustrate the feasibility of assessing the impacts of ICT use on individual activity opportunities under a space-and-time context. Specifically, this chapter employs the concepts of capability constraints and coupling constraints in the classical time geography to examine the ICT impact on F2F meeting opportunities (Hägerstrand 1970, Lenntorp 1976, Forer *et al*., 2007). The main objectives of this chapter include: (1) development of a spatio-temporal analytical framework based on the time geography concepts for assessing potential F2F meeting opportunities under different phone access scenarios, as well as examining their dynamic changes over time, and (2) implementation of the analytical framework in a space-time GIS that offers exploratory analysis functions to investigate the dynamic effects of different phone access on F2F meeting opportunities.

This chapter first presents a time-geographic framework to assess the potential F2F meeting opportunities between two people based on their phone access and dynamic activity scheduling. It then discusses the ICT impacts on potential F2F meeting opportunities under four phone access scenarios and two dynamic activity scheduling scenarios. This chapter also includes the implementation of the time-geographic analytical approach in a space-time GIS with a synthetic dataset to demonstrate the feasibility of the proposed approach and the spatio-temporal exploratory functions. The last section offers concluding remarks.

## 3.1 A Time-geographic Analysis Framework

### *3.1.1 Individual activities and face-to-face meeting opportunities*

As discussed in Chapter 2, under current time-geographic analytical framework, individual activities are usually treated as fixed or flexible activities, based on their degree of flexibility in space and time. Among the fixed activities, some of them take place at a fixed location and time on a regular basis. This study defines such activities as *routine fixed activities*. As Figure 3.1a shows, a geography professor has office hours from 9:00 AM through 11:00 AM every Tuesday in her office, and teaches a transportation geography class in a particular classroom from 3:00 PM to 4:00 PM on every Tuesday. This professor sometimes may have other fixed activities that are not considered as her routine activities. For example, she receives a phone call on a Tuesday morning and is informed that there will be a meeting from 1:00 PM to 2:00 PM in the Dean's office this afternoon (Figure 3.1a). Since this meeting has a fixed location and time, it also is considered a fixed activity. However, this is an occasional event that occurs only on a particular Tuesday, we name it a *non-routine fixed activity*. Besides the routine and non-routine fixed activities, this professor can schedule other activities during her unoccupied time windows. These activities do not have to take place at a particular time and/or location, they are called *flexible activities*.

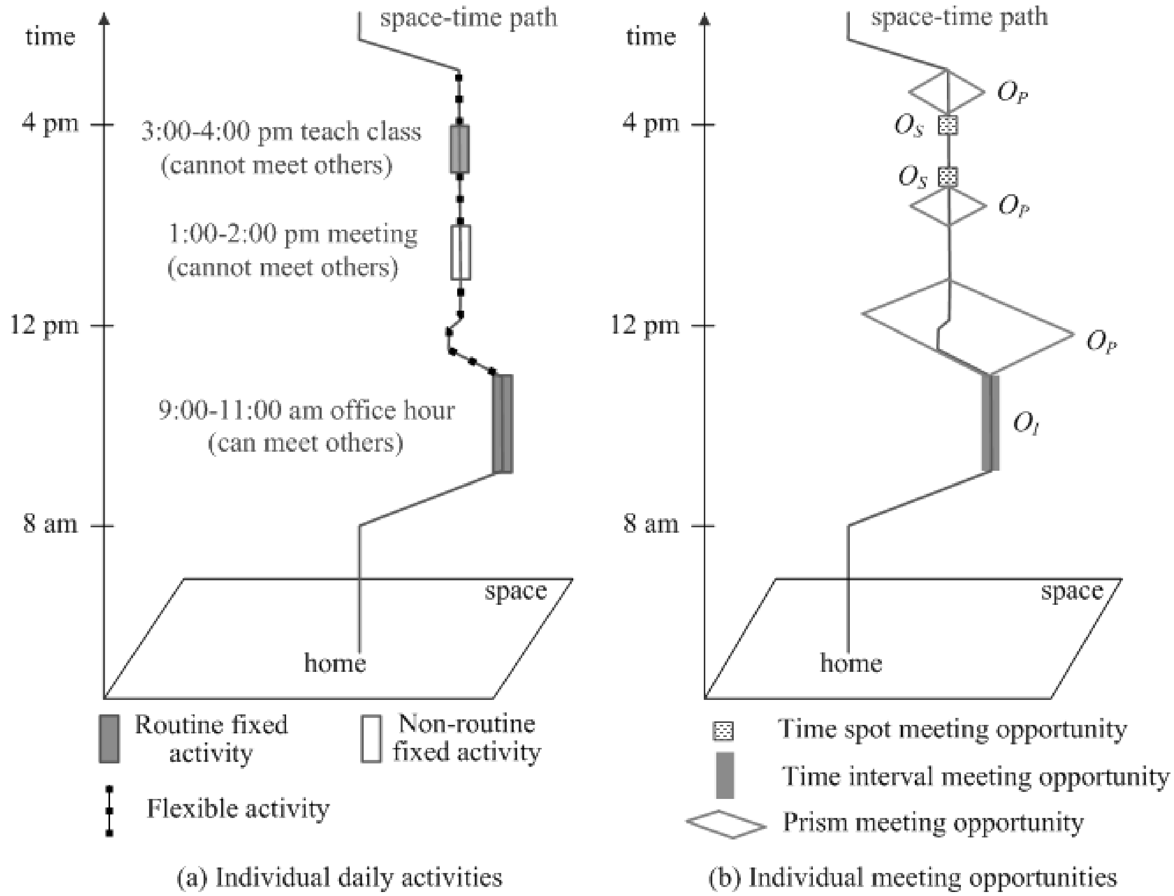



Figure 3.1 The three types of individual daily activities and three types of potential F2F meeting opportunities

In this study, we also define three types of meeting opportunities. First, it is possible to have a F2F meeting with other people during the period of certain fixed activities. For example, a professor can meet with students during her office hours. Such opportunities are defined as *time interval meeting opportunities* $O_I$ (Figure 3.1b). Other types of fixed activities (e.g., teaching a class) prevent people from having a F2F meeting at the same time. Under this circumstance, if person A does not have a prearrangement with person B but needs to see person B, person A has options of catching person B either immediately before or after person B's fixed activity. This study calls such meeting opportunities as *time spot meeting opportunities* $O_S$ (Figure 3.1b).

Finally, F2F meeting opportunities can be defined by a space-time prism during someone's flexible time windows. They are known as *prism meeting opportunities* $O_P$ in this study (Figure 3.1b).

### *3.1.2 Dynamic activity scheduling*

People's planned fixed activities change over time in a day. With the convenience of telecommunication in the ICT age, more activities are based on ad hoc decisions. Ad hoc activities facilitated by ICT reflect an important effect of ICT on daily lives. To assess such impact, this study incorporates dynamic activity scheduling into the analytical framework.

This study refers to planned routine and non-routine fixed activities as *planned activities*. People also plan for their flexible activities, but flexible activities are excluded from planned activities in this analytical framework because they do not serve as anchor points in an activity schedule. Planned activities evolve over time, so they associate with a particular moment (e.g., 8:00 AM, or 6:00 PM). In contrast, the activities an individual has done are referred to as *actual activities*, which include both fixed and flexible activities. An individual's future time windows consist of fixed activity time windows and flexible time windows. At a particular moment of a day $t_0$, compared with the latest activity plan, an individual situates either *in plan* or *out of plan* status. At any moment, if an individual is conducting a planned activity, or is conducting any activity during his/her flexible time windows and is able to make the next planned activity, this individual is considered within an *in plan* status. Otherwise, the individual is regarded as in an *out of plan* status. The status judgment steps are shown in Figure 3.2. With either status, an individual can *keep plan* or *update plan*. For an individual in plan, an update plan action means that he/she will deviate from planned fixed activities or add new fixed activities in the rest of the day. For an individual already out of plan, a keep plan action means he/she will return to the planned activities as soon as possible. For instance, a person is trapped by traffic congestion on her way to a meeting. She is already late for the meeting and is out of plan. If she still keeps her meeting plan, she probably will inform other attendants of her late arrival, and keep driving to the meeting.

Given a $t_0$ moment in a day, an individual's potential meeting opportunities after $t_0$ depend on his/her current activity status and the action of scheduling future planned activities.

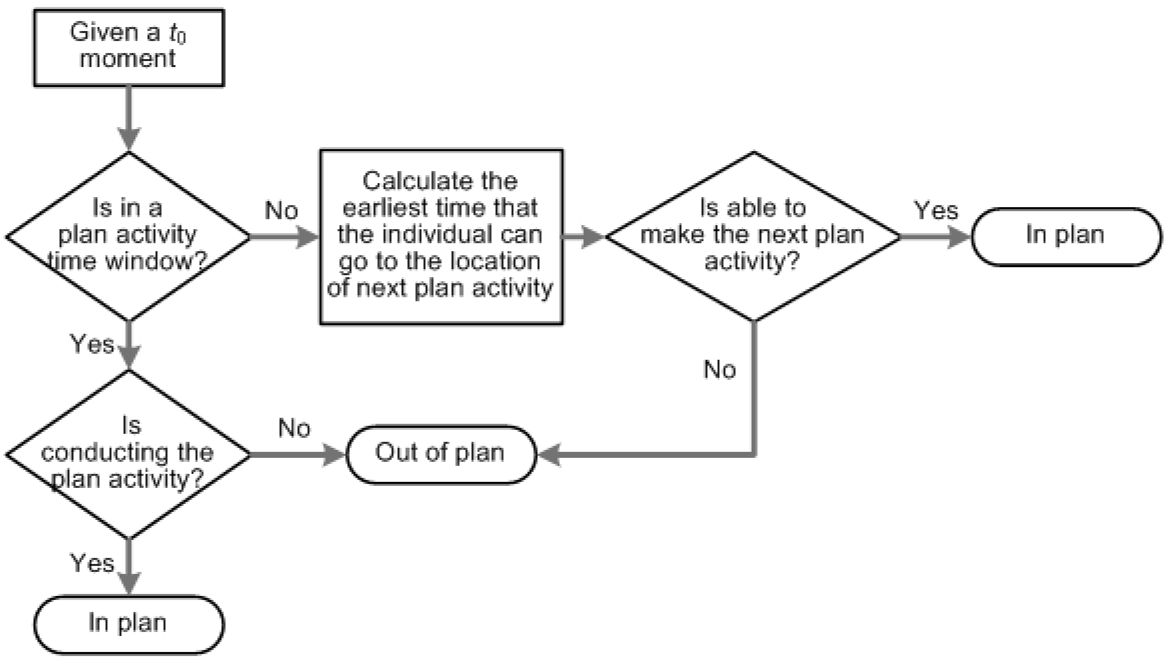



Figure 3.2 Activity status judgment steps

### *3.1.3 ICT communication modes and their space-time constraints*

Among various possible ICT communication modes, this study uses phone communications as an example to illustrate the effects of virtual communications on physical communication opportunities. Specifically, this study considers two types of phone devices: landline phones and mobile phones. Landline phones are tied to fixed locations (e.g., home or office); therefore, access to a landline phone is available at particular locations only. On the other hand, mobile phones allow people to stay in touch at all locations except for situations such as out of service area or out of battery power. This study examines the impacts on F2F meeting opportunities under four different scenarios of phone access levels, which include *no access to phone service*, *landline phone service only for both persons*, *landline phone service for one person and mobile phone service for the other person*, and *mobile phone service for both persons*.

All phone communications involve a sender and a receiver. This study defines the time windows in which a person can make a phone call or send a voice/text message as *send time windows* ($T_S$) and the time windows in which a person can receive a phone call or access a voice/text message as *receive time windows* ($T_R$). When two people attempt to arrange a F2F meeting via phone communications, they need at least one *complete phone communication* to confirm their arrangement. A complete phone communication is defined as a two-way information exchange, consisting of an initial information delivery from person A to person B and an information delivery from person B back to person A. For example, if two people are talking over phones, person A asks person B whether they can meet at seven o'clock this evening. This phone communication is considered complete only after person B has responded to person A's request. If person A leaves a voice message to person B with suggested meeting time and location, this phone communication is not complete until person A receives a response from person B. Figure 3.3 shows three different possible ways of completing a phone communication via synchronous and asynchronous communications. We should note that one complete phone communication does not guarantee the final arrangement of a F2F meeting. For example, people sometimes need to call each other multiple times to rearrange a meeting. Since this study is to assess all potential F2F meeting opportunities between two people, we will identify all potential F2F meeting opportunities after one complete phone communication. All subsequent phone communications to rearrange a meeting simply reduce the meeting opportunity space to a subset of its original opportunity space.

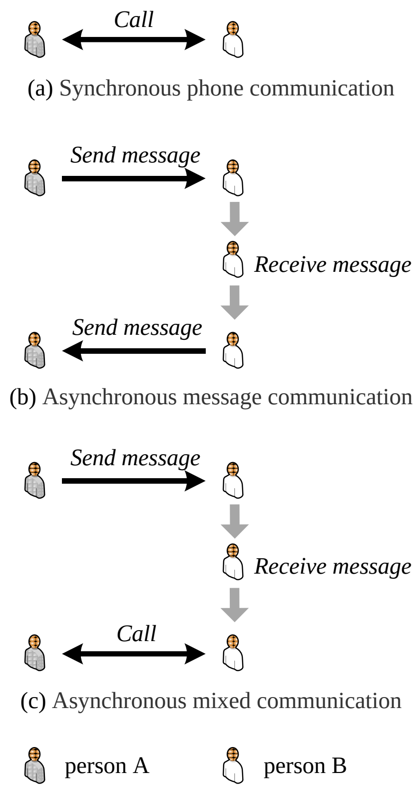



Figure 3.3 Three modes of a complete phone communication

### *3.1.4 Potential face-to-face meeting opportunities*

This study uses one full day (24 hours) as the timeframe of analyzing potential interactions between two people. It can be adjusted to a longer period or a shorter period depending on the application needs. To illustrate how this time-geographic analytical framework works, we assume the following conditions in the example used here. First, we assume that at moment $t_0$ person A needs to have a F2F meeting with person B in the day, yet person A does not have a prearrangement with person B for this meeting. Second, both persons know each other's daily routine fixed activities, but they do not know each other's latest planned activities unless they can communicate with each other. Therefore, person A can figure out all potential meeting opportunities with person B based on person A's knowledge of person B's routine fixed activities. However, if person B deviates from his routine fixed activities or engages in other activities during his flexible time windows, person A will not know where to find person B unless they can have a complete phone communication. Finally, we assume that they know each other's landline/mobile phone numbers.

Whether or not these two persons can have a complete phone communication after $t_0$ plays a critical role regarding their potential F2F meeting opportunities. If both persons do not have access to phones, they can only count on their knowledge of the other person's routine fixed activities to try to catch each other. On the other hand, if they have access to either landline phones or mobile phones, it becomes feasible for them to communicate with each other. Mobile phones clearly offer a higher level of spatial and temporal flexibility than landline phones to reach other people or be reached by other people. This paper shows how we can assess all potential F2F meeting opportunities between two people when they complete a phone communication. Since our focus is on finding the maximum possible potential meeting opportunities, the earliest possible time of completing a phone communication ($t_c$) therefore serves as an important parameter in the presented analytical framework.

The following subsections will first present an approach of calculating $t_c$ for each type of a complete phone communication (Figure 3.3). Then they will present an approach of analyzing potential F2F meeting opportunities before and after a complete phone communication. Before calculating $t_c$, we need to define the send time windows and the receive time windows for each person after $t_0$:

$$T_S{}^{A}{}_{(t>t_0)} = \bigcup_{i=1} \{(t^{A}_{S\_start})_i, (t^{A}_{S\_end})_i\}_{(t>t_0)},\ i \in N^+ \tag{3-1}$$

$$T_R{}^{A}{}_{(t>t_0)} = \bigcup_{j=1} \{(t^{A}_{R\_start})_j, (t^{A}_{R\_end})_j\}_{(t>t_0)},\ j \in N^+ \tag{3-2}$$

$$T_S{}^{B}{}_{(t>t_0)} = \bigcup_{k=1} \{(t^{B}_{S\_start})_k, (t^{B}_{S\_end})_k\}_{(t>t_0)},\ k \in N^+ \tag{3-3}$$

$$T_R{}^{B}{}_{(t>t_0)} = \bigcup_{l=1} \{(t^{B}_{R\_start})_l, (t^{B}_{R\_end})_l\}_{(t>t_0)},\ l \in N^+ \tag{3-4}$$

where

$i, j, k, l$ are indices of time windows in different sets;

$T_S{}^{A}{}_{(t>t_0)}$ is the set of send time windows of person A after $t_0$;

$T_R{}^{A}{}_{(t>t_0)}$ is the set of receive time windows of person A after $t_0$;

$T_S{}^{B}{}_{(t>t_0)}$ is the set of send time windows of person B after $t_0$;

$T_R{}^{B}{}_{(t>t_0)}$ is the set of receive time windows of person B after $t_0$;

$\{(t^{A}{}_{S\_start})_i, (t^{A}{}_{S\_end})_i\}_{(t>t_0)}$ are the start time and end time in each send time window for person A after $t_0$;

$\{(t^{A}{}_{R\_start})_j, (t^{A}{}_{R\_end})_j\}_{(t>t_0)}$ are the start time and end time in each receive time window for person A after $t_0$;

$\{(t^{B}{}_{S\_start})_k, (t^{B}{}_{S\_end})_k\}_{(t>t_0)}$ are the start time and end time in each send time window for person B after $t_0$;

$\{(t^{B}{}_{R\_start})_l, (t^{B}{}_{R\_end})_l\}_{(t>t_0)}$ are the start time and end time in each receive time window for person B after $t_0$.

**(1) Synchronous phone communication**

For the first type of phone communication (Figure 3.3 (a)), the method of finding the earliest time to finish a synchronous phone communication after $t_0$ between person A and person B ($t_{c1}$) is described below (Figure 3.4 (a)):

Step 1: calculate the intersection of the set of send time windows for person A and the set of receive time windows for person B;

if $T_S{}^{A}{}_{(t>t_0)} \cap T_R{}^{B}{}_{(t>t_0)} \neq \varnothing$

then

$$T_S{}^{A}{}_{(t>t_0)} \cap T_R{}^{B}{}_{(t>t_0)} = \bigcup_{m=1} \{(t^{*}{}_{start})_m, (t^{*}{}_{end})_m\}_{(t>t_0)},\ m \in N^{+} \tag{3-5}$$

where

$m$ is an index of a set of time windows;

$\{(t^{*}{}_{start})_m, (t^{*}{}_{end})_m\}_{(t>t_0)}$ indicates the start time and the end time in each time window when person A can call person B after $t_0$.

Step 2: calculate $t_{c1}$;

$$t_{c1} = \min((t^{*}{}_{start})_m)_{(t>t_0)} \tag{3-6}$$

where

$\min((t^{*}_{start})_m)_{(t>t_0)}$ finds the earliest start time in all time windows when person A can call person B.

**(2) Asynchronous message communication**

For the second type of phone communication (Figure 3.3b), the procedure of finding the earliest time to finish an asynchronous message communication after $t_0$ between person A and person B ($t_{c2}$) is given below (Figure 3.4 (b)):

Step 1: identify the first send time window for person A (${T_{S1}}^{A}{}_{(t>t_0)}$);

Step 2: find the earliest receive time window (${T_{Ri}}^{B}{}_{(t>t_0)}$) when person B can receive the message sent from person A;

Step 3: find the earliest send time window (${T_{Sj}}^{B}{}_{(t>t_0)}$) when person B can send a message back to person A;

Step 4: find the earliest receive time window (${T_{Rk}}^{A}{}_{(t>t_0)}$) when person A can receive the feedback message sent from person B;

Step 5: calculate $t_{c2}$;

$$t_{c2} = (t^{A}_{R\_start})_k \tag{3-7}$$

where

$(t^{A}_{R\_start})_k$ is the start time in the earliest receive time window (${T_{Rk}}^{A}{}_{(t>t_0)}$) when person A can receive the feedback message sent from person B.

**(3) Asynchronous mixed communication**

For the third type of phone communication (Figure 3.3c), the procedure of finding the earliest time to finish an asynchronous mixed communication after $t_0$ between person A and person B ($t_{c3}$) is described below (Figure 3.4c):

Step 1: identify the first send time window for person A (${T_{S1}^{A}}_{(t>t_0)}$);

Step 2: find the earliest receive time window (${T_{Ri}^{B}}_{(t>t_0)}$) when person B can receive the message sent from person A;

Step 3: find the earliest send time window (${T_{Sj}^{B}}_{(t>t_0)}$) when person B can call back to person A;

Step 4: calculate the intersection set of (${T_{Sj}^{B}}_{(t>t_0)}$) and the set of receive time windows for person A;

$$\text{if } {T_{Sj}^{B}}_{(t>t_0)} \cap {T_{R}^{A}}_{(t>t_0)} \neq \varnothing$$

$$\text{then } {T_{Sj}^{B}}_{(t>t_0)} \cap {T_{R}^{A}}_{(t>t_0)} = (t_{start}^{**}, t_{end}^{**})_{(t>t_0)} \tag{3-8}$$

where

$(t_{start}^{**}, t_{end}^{**})_{(t>t_0)}$ indicates the start time and the end time in the earliest time window when person B can call person A after person B receives the message from person A.

Step 5: calculate $t_{c3}$;

$$t_{c3} = {t^{**}}_{start} \tag{3-9}$$

Finally, the earliest time of finishing a complete phone communication after $t_0$ between two persons ($t_c$) is:

$$t_c = \min\{t_{c1}, t_{c2}, t_{c3}\},\quad t_c > t_0 \tag{3-10}$$

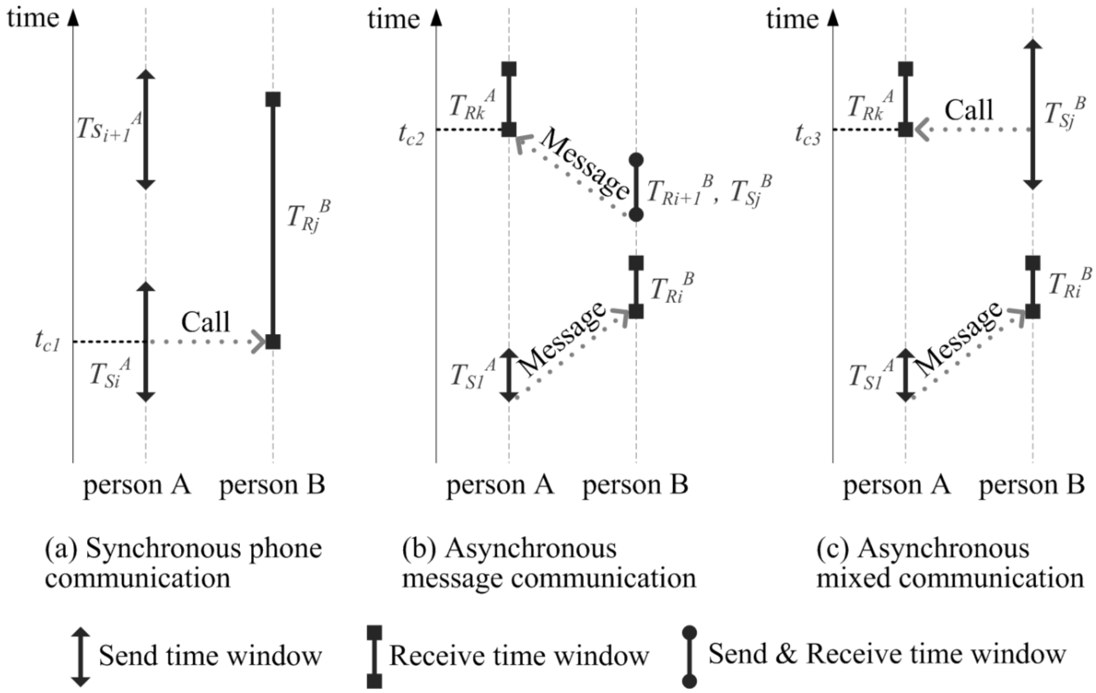



Figure 3.4 Examples for a complete phone communication

In the case that person A wants to meet with person B without phone access, person A must rely on his/her knowledge of person B's routine fixed activities to find person B. In other words, only the time interval meeting opportunities and time spot meeting opportunities based on person B's routine fixed activities are perceived by person A as potential meeting opportunities. Even though there may be available prism meeting opportunities during their flexible time windows, person A cannot take advantage of such opportunities because they cannot communicate with each other. If person B changes his routine fixed activities, their F2F meeting opportunities may further shrink. Therefore, the potential F2F meeting opportunities $\bar{O}_{(t>t_0)}$ between person A and person B when they do not have phone access are defined as follows:

$$\bar{O}_{(t>t_0)} = O^{A}{}_{(t>t_0)} \cap O^{B/A}{}_{(t>t_0)} \tag{3-11}$$

where

$O^{A}{}_{(t>t_0)} = O^{A}_{S\,(t>t_0)} \cup O^{A}_{I\,(t>t_0)} \cup O^{A}_{P\,(t>t_0)}$;

$O^{B/A}{}_{(t>t_0)} = O^{B/A}_{S}{}_{(t>t_0)} \cup O^{B/A}_{I}{}_{(t>t_0)}$;

$O^{A}{}_{(t>t_0)}$ is person A’s full meeting opportunity set after $t_0$;

$O^{A}_{S\,(t>t_0)}$ is person A’s time spot meeting opportunity set after $t_0$;

$O^{A}_{I\,(t>t_0)}$ is person A’s time interval meeting opportunity set after $t_0$;

$O^{A}_{P\,(t>t_0)}$ is person A’s prism meeting opportunity set after $t_0$;

$O^{B/A}{}_{(t>t_0)}$ is person B’s full meeting opportunity set after $t_0$ perceived by person A;

$O^{B/A}_{S}{}_{(t>t_0)}$ is person B’s time spot meeting opportunity set after $t_0$ perceived by person A;

$O^{B/A}_{I}{}_{(t>t_0)}$ is person B’s time interval meeting opportunity set after $t_0$ perceived by person A.

If persons A and B can finish a complete phone communication at $t_c$, they will know feasible F2F meeting opportunities after $t_c$ according to their planned activities. In this situation, their potential F2F meeting opportunity set becomes the intersection of their respective potential meeting opportunity sets modified by their planned activities, which might have been changed over time and include non-routine fixed activities. Compared with the potential meeting opportunities perceived by person A before the time they completed a phone communication, the potential meeting opportunity set now includes the meeting opportunities based on not only person B’s routine fixed activities but also his planned non-routine fixed activities that could not be known without a complete phone communication. In addition, they could arrange a F2F meeting in the prism meeting opportunity set. Their potential F2F meeting opportunities $\tilde{O}_{(t>t_c)}$ is:

$$\tilde{O}_{(t>t_c)} = O^{A}{}_{(t>t_c)} \cap O^{B}{}_{(t>t_c)} \qquad (3\text{-}12)$$

where

$$O^{B}{}_{(t>t_0)} = O^{B}_{S\,(t>t_0)} \cup O^{B}_{I\,(t>t_0)} \cup O^{B}_{P\,(t>t_0)}$$

Finally the potential F2F meeting opportunities $O_{(t>0)}$ for person A and person B after $t_0$ is:

$$O_{(t>t_0)} = \bar{O}_{(t>t_0)} \cup \tilde{O}_{(t>t_c)}, \quad t_c > t_0 \tag{13}$$

## 3.2 Scenario Analysis

The above analysis framework is used to explore the impacts of phone communication modes on dynamic F2F meeting opportunities in a day. This section will first analyze potential F2F meeting opportunities for a given $t_0$ under four phone access scenarios. It then will analyze changing potential F2F meeting opportunities over time with a particular phone access under two dynamic scheduling scenarios.

### *3.2.1 Different phone access scenario analysis*

In the phone access scenario analysis, $t_0$ is set at 8:00 AM on a Monday. At 8:00 AM, person A knows that he has three routine fixed activities to do on Monday and no changes have occurred so far. Person B also has three routine fixed activities on Monday, but in the morning he already knows that he cannot attend the regular meeting at his office in the afternoon because he will stay in his lab longer than usual. Since he can meet with others at his lab, this non-routine fixed activity at his lab opens an extra time interval meeting opportunity for person B. The four phone access scenarios are: (1) neither person has phone access during the day; (2) neither person carries a mobile phone, but both people have access to landline phones; (3) person A carries a mobile phone, but person B has access to landline phones only; and (4) both persons carry a mobile phone.

The first scenario is a benchmark case that assumes both persons do not have access to either landline or mobile phones at all. This benchmark scenario allows us to evaluate how different levels of phone access affect a person's F2F meeting opportunities. Figure 3.5a1 shows the two persons' space-time paths according to their tentative activity plan at 8:00 AM. In addition, an individual can easily change his/her flexible activities, so the space-time prisms around person A's space-time path represent person A's potential spatio-temporal extents of having a F2F meeting with person B. Since neither person has phone access, person A has no way of knowing that person B stays longer at the lab than he usually does. As a result, person A cannot perceive the additional time interval meeting opportunity with person B in the afternoon that becomes feasible because of person B's non-routine extended stay at the lab. In this case, the only F2F meeting opportunity with B that can be perceived by person A is the time interval meeting opportunity window in the morning (Figure 3.5a2).

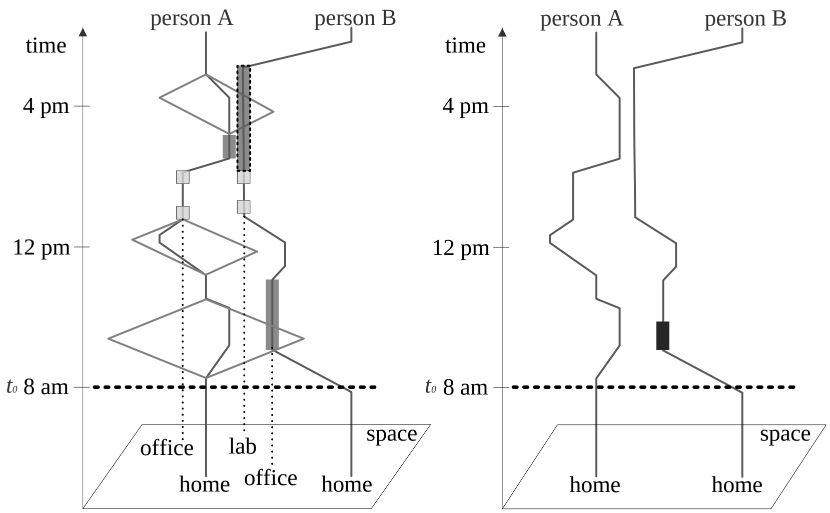
In the second scenario (Figure 3.5b1), both person A and person B have access to landline phones at particular locations (e.g. home, office, lab). Before person A leaves home in the morning, she can leave a voice message on person B's office phone. When person B returns a phone call during the time window $T_{R1}{}^{B}$, person A is out of her home. The earliest possible time that person A can receive the message left by person B therefore is at $T_{R2}{}^{A}$ (i.e., the earliest time they can finish a complete asynchronous message communication, $t_c$). Since it now is feasible for person A to learn from person B that person B will stay longer at the lab, the time interval meeting opportunity in the afternoon becomes a feasible option for them to have a F2F meeting in addition to the meeting opportunity in the morning (Figure 3.5b2).

The third scenario assumes that person A has a mobile phone while person B can only access landline phones at his office and lab. Once person B arrives at his office, person A can reach person B via phone. As a result, the start time of ${T_{R1}}^B$ is the earliest possible time for person A to communicate with person B to make meeting arrangements (i.e. $t_c$ in Figure 3.5c1). In this case, it is feasible for person A to know all possible F2F meeting opportunities after $t_c$, including two time interval meeting opportunity windows and a prism meeting opportunity window around noon (Figure 3.5c2).

In the fourth scenario (Figure 3.5d1), both persons carry a mobile phone, but person B does not turn on his mobile phone until 11:00 AM when he finishes his morning work. Furthermore, we assume that person A does not know person B's work phone number. In this case, 11:00 AM is the earliest possible time for them to communicate and stay in touch (i.e., $t_c$ in Figure 3.5d1). Again, they can meet at any of the two time interval opportunity windows and/or in the prism time opportunity window (Figure 3.5d2).

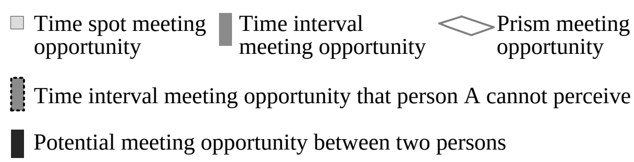
The above four scenarios demonstrate the capability of proposed analysis framework to explicitly evaluate the effects of different phone communication modes on potential F2F meeting opportunities. In addition, this analysis framework can assist researchers to quantitatively assess the spatial and temporal extents on F2F meeting opportunities due to different phone communication access scenarios.

**No phone access**

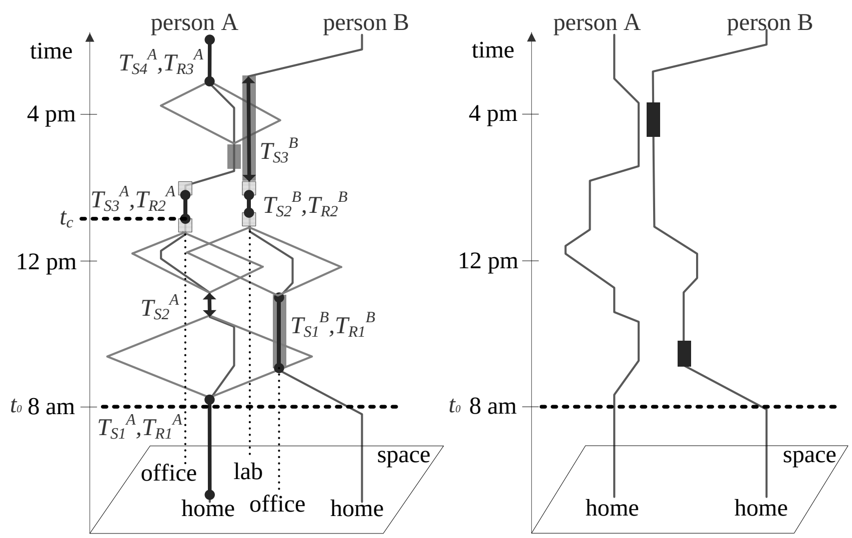



(a1) Person A's potential meeting opportunities and person B's Potential meeting opportunities that can be perceived by person A

(a2) The potential meeting opportunities for person A and person B

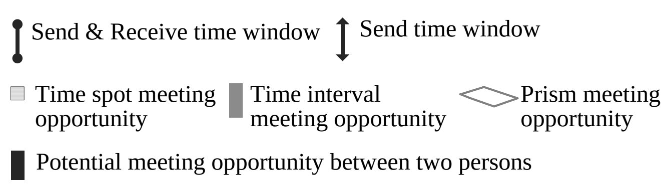



**With landline phones**




(b1) Person A's potential meeting opportunities and person B's potential meeting opportunities

(b2) The potential meeting opportunities for person A and person B



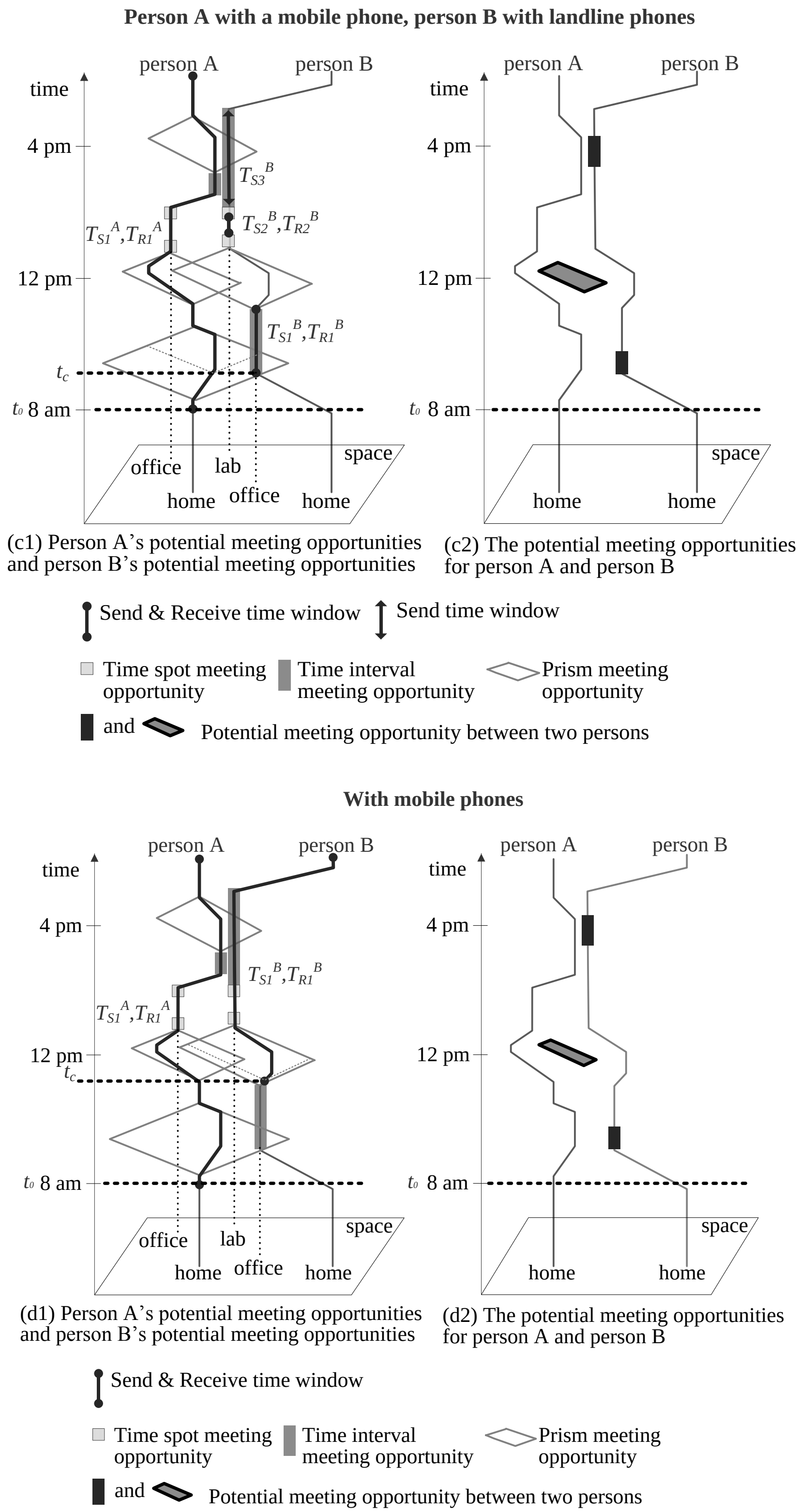



Figure 3.5 The potential F2F meeting opportunities of person A and person B with different phone access

### *3.2.2 Different activity scheduling scenario analysis*

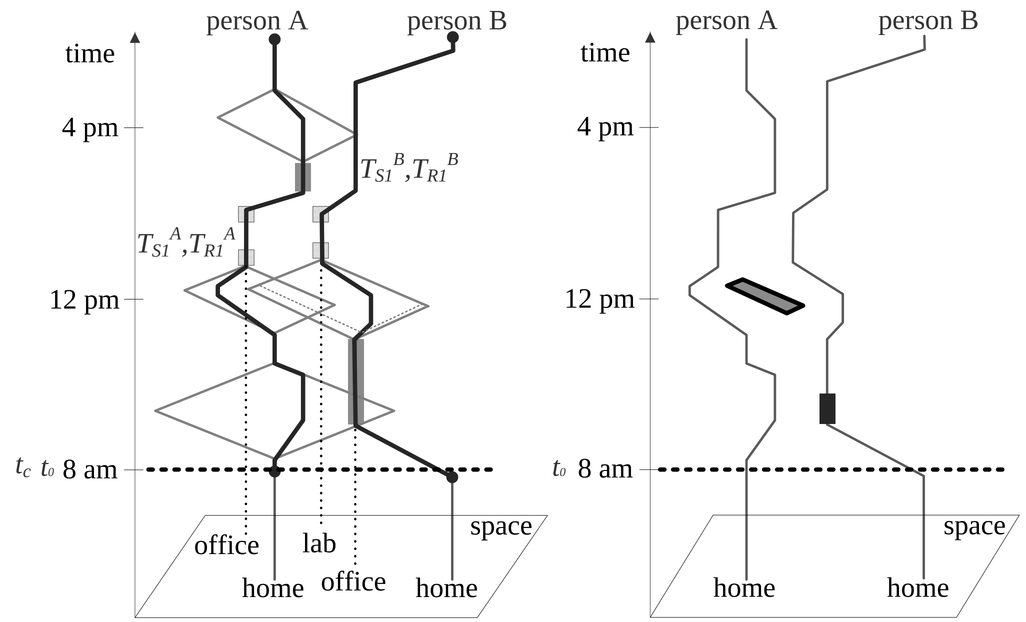
Given both people using a mobile phone all day, this section analyzes the changes of the two persons' potential F2F meeting opportunities over time, under two activity scheduling scenarios: (1) person B does not know when he will finish his lab, and keeps the original plan to go back to his office after lab; (2) at 2:00 PM, person B knows that his lab will last several more hours, and decides to update his plan by not attending the regular meeting and staying at the lab instead.

In the first scenario, at 8:00 AM in the morning, person B is not aware of the changes in his routine activities in the afternoon. If person A calls him at 8:00 AM, their potential F2F meeting opportunities include the time interval meeting opportunity in the morning and the prism meeting opportunity during lunch time (Figure 3.6a1 and a2). If person A does not call person B until 12:00 PM, although they both have some flexible time after lunch and before work in the afternoon, the flexible time left is not enough for them to have a F2F meeting (Figure 3.6b1). In addition, person B is still not aware of the change in his routine activities in the afternoon. As a result, they do not have potential F2F meeting opportunities left (Figure 3.6b2). If person A calls person B at 2:10 PM, person B is still at lab instead of on his way to the regular meeting. Person B is already in an out of plan status, but he still keeps the original plan to try to get back to the regular meeting. Accordingly, they do not have any potential F2F meeting opportunities (Figure 3.6c1 and c2).

In the second scenario, person B updates his plan at 2:00 PM. When person A calls him at 12:00 PM, they do not have potential F2F meeting opportunities. However, when person A calls him at 2:10 PM, person B will tell person A the change of his plan, and they will have an interval meeting opportunity in the afternoon (Figure 3.6d1 and d2). This is an example of an ad hoc arrangement facilitated by telecommunication.

The above two scenarios demonstrate the capability of proposed analysis framework to catch the dynamic changes in potential F2F meeting opportunities with activity scheduling change over time. It articulates the way people use ICT to dynamically arrange their activities.

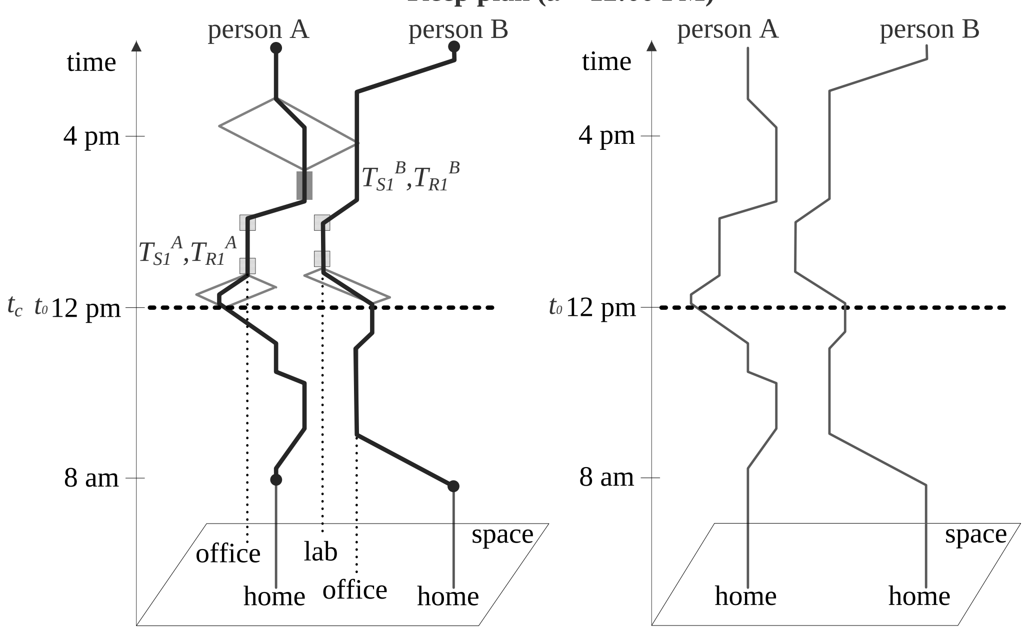
**Keep plan ($t_0$ = 8:00 AM)**




(a1) Person A's potential meeting opportunities and person B's potential meeting opportunities

(a2) The potential meeting opportunities for person A and person B

**Keep plan ($t_0$ = 12:00 PM)**




(b1) Person A's potential meeting opportunities and person B's potential meeting opportunities

(b2) The potential meeting opportunities for person A and person B

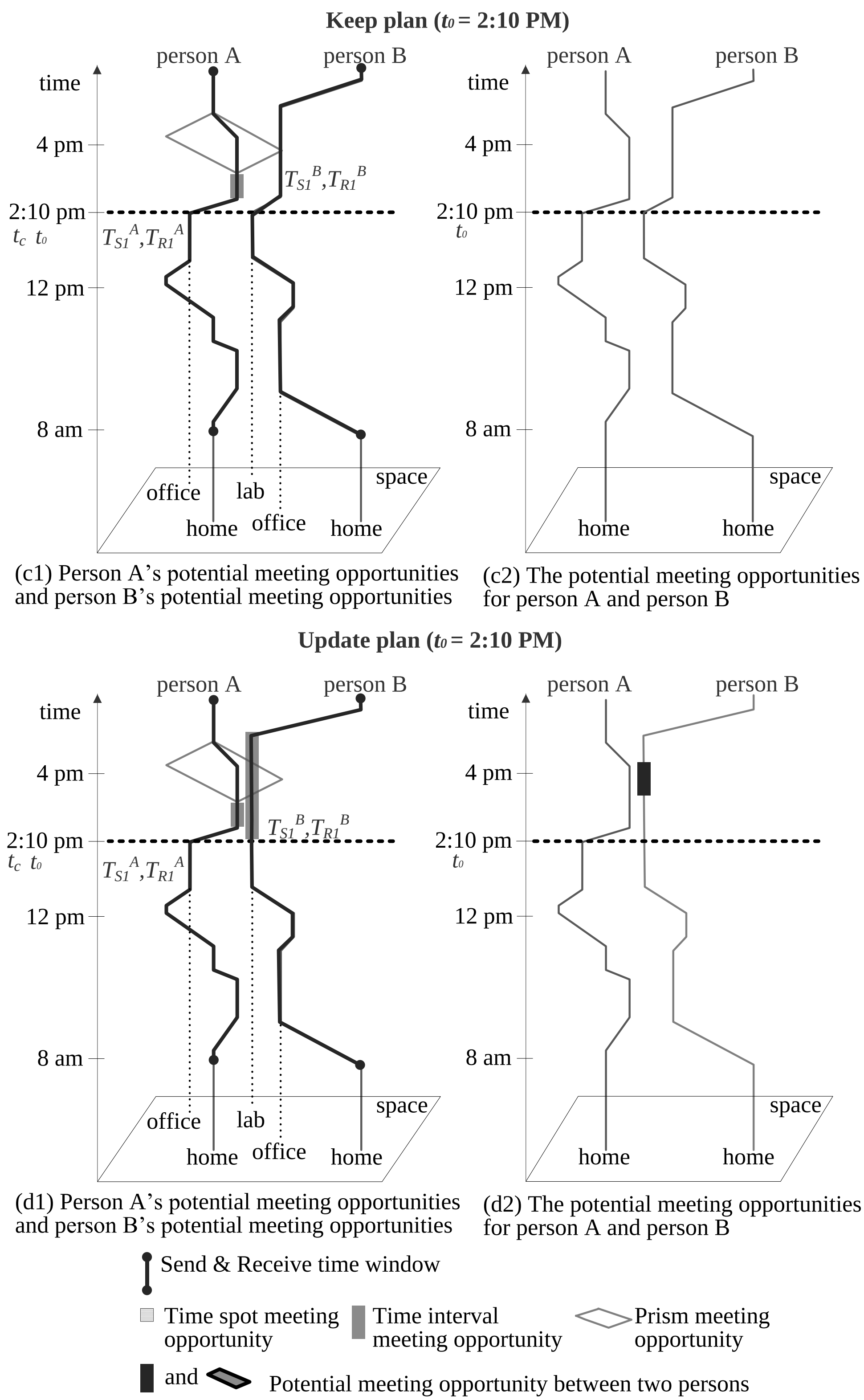


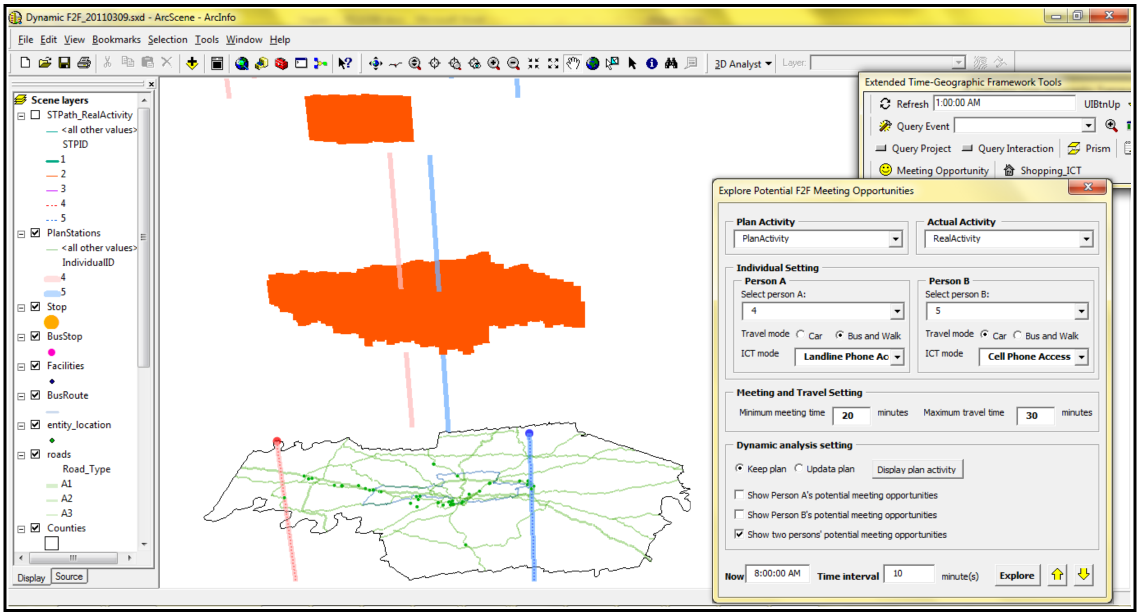

Figure 3.6 The potential F2F meeting opportunities of person A and person B with different activity scheduling

## 3.3 A Space-time GIS Prototype

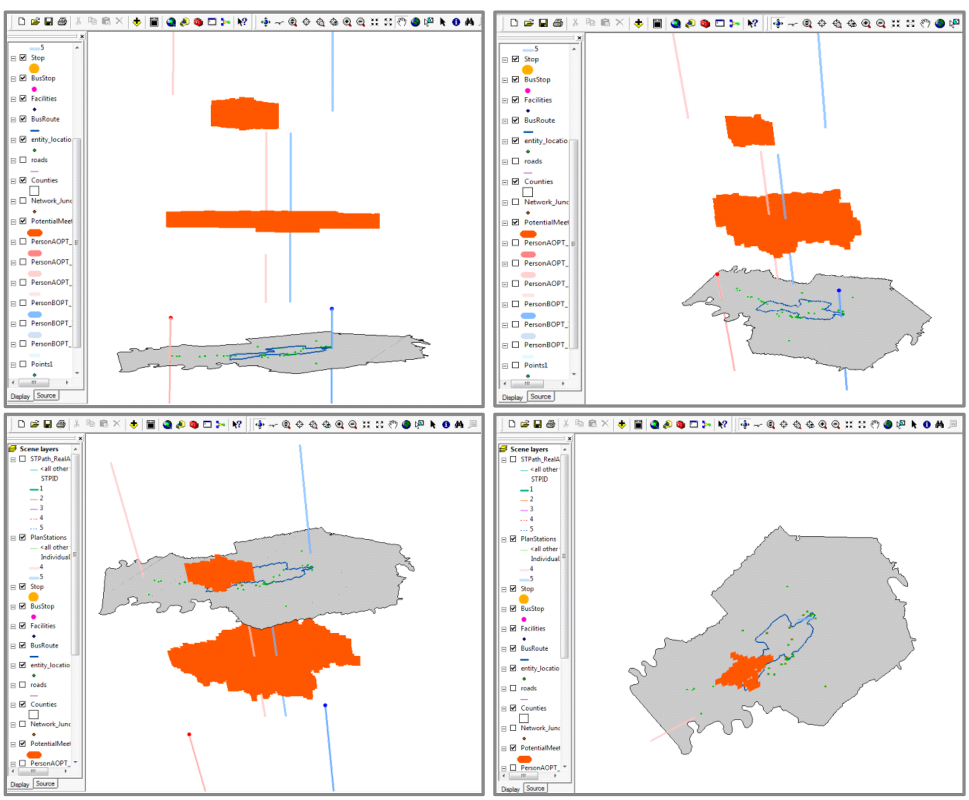
### *3.3.1 A space-time GIS prototype*

There have been a number of studies with GIS implementations of space-time paths and space-time prisms (e.g., Miller, 1991; Kwan, 2000, 2004; Buliung and Kanaroglou, 2006; Yu, 2006; Neutens *et al*., 2007b; Shaw *et al*., 2008; Yu and Shaw 2008; Miller and Bridwell, 2009;Shaw and Yu, 2009). Although these studies have made significant progress on GIS implementation of time geography concepts, they have not explicitly considered the impacts of communication modes on human interaction opportunities. This study builds on and extends the space-time GIS prototype system of Shaw and Yu (2009) to assess the influence of different phone access levels on F2F meeting opportunities.

Based on a temporal dynamic segmentation design in the 3D environment of ArcScene (Environmental Systems Research Institute, Redland, CA), this prototype system uses x and y dimensions for spatial representation, and z dimension for temporal representation (Figure 3.7). A space-time path is visualized as a 3D polyline. A space-time prism is represented with a set of vertical 3D polylines extruded from the transportation network junctions that are accessible under spatio-temporal constraints (see Yu and Shaw, 2008 for details). The potential F2F meeting places within a space-time prism are represented by transportation network junctions, which are used as surrogates for real points of interests. Time spot meeting opportunities appear in pairs, defined as two five-minute windows before and after a fixed activity. A time interval meeting opportunity is a vertical line whose length is determined by the time period of a fixed activity. A prism meeting opportunity is created by a space-time prism, which consists of a set of vertical lines, whose lengths represent the maximum available activity time at each network location. Potential F2F meeting opportunities between two or more persons can be evaluated by checking if their potential meeting opportunities overlap.




(a) The space-time GIS environment



(b) Different observation angles in the space-time GIS environment

Figure 3.7 The space-time GIS prototype

The Tool for exploring potential F2F meeting opportunities with dynamic scheduling needs a planned activity table and an actual activity table as input (Figure 3.8). Several data sources provide actual activity records, such as a daily activity diary and GPS/cell phone/mobile device tracking data. Compared with actual activity records, planned activities are more subjective and are more difficult to obtain. An individual's routine activities can be considered as a basis of planned activities. With people's long-term tracking data, it is possible to detect their routine activities within a period (Patterson *et al*., 2003; Gidófalvi and Pedersen, 2009). It is also possible to obtain activity plans from digital planning assistants, such as an alert service based on a location-based service (e.g., http://www.estimotion.com/). The way of setting the two input tables is adjustable to applications (Table 3.1).

Table 3.1 Different applications of the Tool for exploring potential F2F meeting opportunities

| Data source | Planned activity setting | Actual activity setting | Application |
|---|---|---|---|
| Daily activity diary | Daily activity diary | Daily activity diary | Retrospective analysis |
| Long-term tracking data | Routine activities retrieved from long-term tracking data | Routine activities retrieved from long-term tracking data | Deductive analysis |
| | Routine activities retrieved from long-term tracking data | Actual activity in a day | Dynamic scheduling simulation |
| Real-time tracking data | Activity plan set by users | Updated plan set by users | Real-time location-based service |

For a connected group, if their activity diaries for a short term (e.g., one day or several days) are available, we can construct their actual activity tables. Since it is a short-term survey, their routine activities are unknown. In this case, their dynamic scheduling process cannot be deduced. However, if their actual activities are set both in the planned activity table and the actual activity table, the Tool offers a retrospective analysis. For instance, by setting the current time as 0:00 AM in the morning, the Tool can calculate and visualize all potential F2F meeting opportunities during entire day between two persons according to their actual activities. These potential F2F meeting opportunities are the opportunities they could have.

With long-term tracking data, the Tool allows deductive analysis and dynamic scheduling simulation. If we deduce routine activities from long-term tracking data, and set routine activities as both planned and actual activities, we assume people live a regular day without any ad hoc changes. With such an assumption, the potential F2F meeting opportunities analyzed by the Tool are a product of deductive reasoning based on people's routine activities. If one particular day's actual activities are set as the actual activities in the Tool, the actual activities could be different from the routine activities. In that case, we can simulate people's dynamic activity scheduling and analyze the changes in F2F meeting opportunities over time.

The Tool also can serve location-based applications. If two persons enter their planned activities into their mobile devices, which connect to the GIS analysis server, the GIS server is able to suggest meeting places and meeting times for them. Once the GIS server detects a user is out of plan, the LBS can alter this user, and offer him/her options to update the original plan.

With a proper sample, retrospective analysis, deductive analysis, and dynamic scheduling simulation are able to compare physical interaction space for people with different ICT access, different demographics (e.g., income, education, age), and different travel patterns (e.g., commuting pattern). Comparing people's actual F2F meetings and their potential meeting opportunities can help understand human behavior in arranging interaction activities.

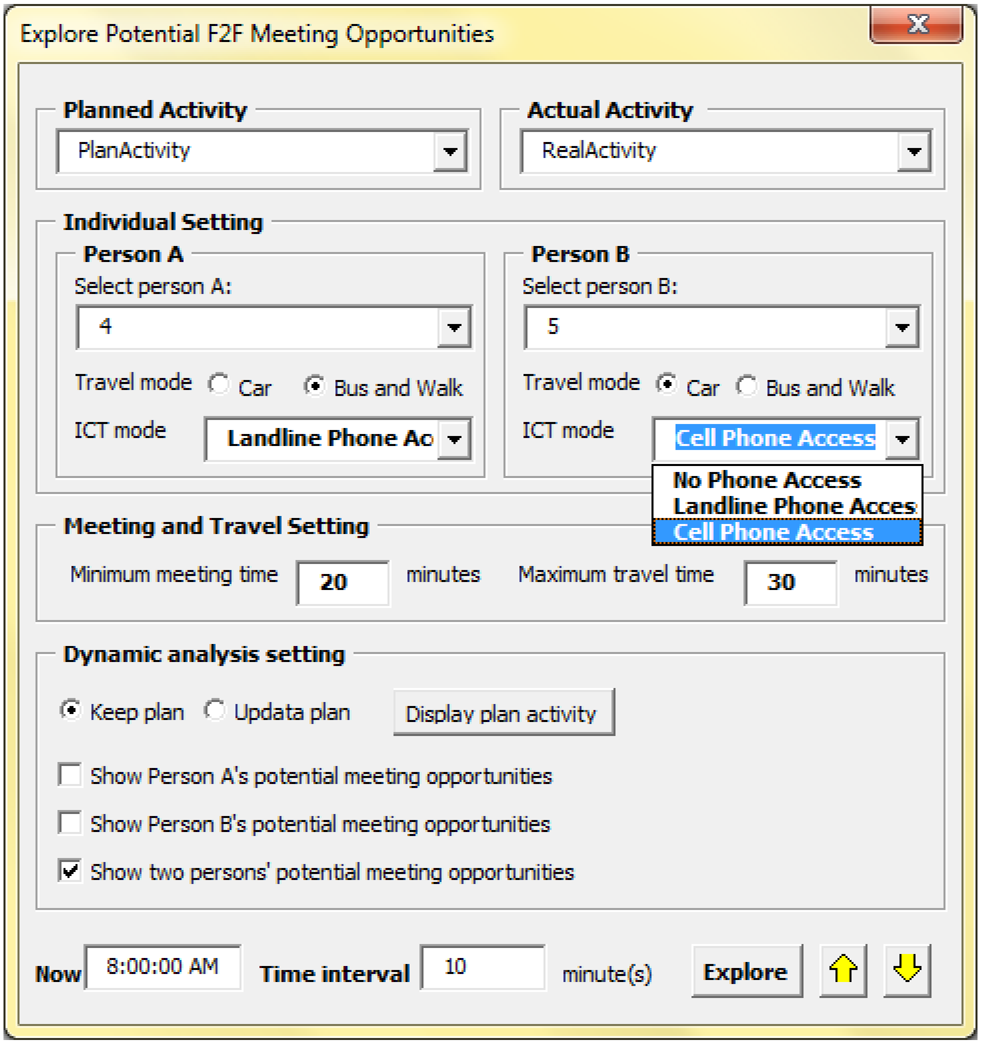



Figure 3.8 The Tool for exploring potential F2F meeting opportunities

Users are able to set their own parameter values on the Tool's interface, including individuals of interest, travel mode, phone access mode, minimum meeting time, maximum travel time, activity scheduling actions (keep plan or update plan), and current time $t_0$ (Figure 3.8). They also can choose how to display the results. It offers the ability to check each person's own potential F2F meeting opportunities, as well as the potential F2F meeting opportunities between two persons, including when person A can find person B and vice versa.

This study chooses Knox County, Tennessee as an example to illustrate the space-time GIS implementation. Three alternative travel modes (private automobile, bus, and walking) are considered in this implementation. Average travel speeds for these three modes are estimated and assigned to network links. Bus routes and the street network are connected at the bus stops.

The following two sections will respectively demonstrate a retrospective analysis and a dynamic scheduling simulation with hypothetical data.

### *3.3.2 A retrospective analysis*

The first case study compares the impacts of different phone communication access on F2F meeting opportunity space for three pairs of people who have different activity patterns and use different transportation modes.

Table 3.2 lists their home location, primary travel mode, and major activities on a particular day. To reveal the impacts of different phone communication modes, this case study illustrates two extreme situations of phone accessibility: no phone access at all versus full-day mobile phone access. The potential F2F meeting opportunities without phone access and with mobile phone access are computed for each pair of the three persons. As a retrospective analysis, their planned activity table and the actual activity table are both set as their actual activity tables, and the current time is set as 0:00 AM (see "Now" textbox on the interface in Figure 3.8). A minimum F2F meeting time (20 minutes) and a maximum travel time for a single trip (30 minutes) are used in this case study.

Table 3.2 Hypothetic daily activities for the three persons

| | person A | person B | person C |
|---|---|---|---|
| Home location | Near UT campus | In East Knox | In West Knox |
| Travel mode | Bus | Car | Car |
| Actual activity | 8:38-9:05 Taking a bus to UT (*RF*, *N*) | 7:25-8:05 Driving a car to office (*RF*, *N*) | 7:20-7:55 Driving a car to office (*RF*, *N*) |
| | 9:15-10:20 Taking a class at UT (*RF*, *N*) | 8:05-9:20 Working in office (*RF*, *Y*) | 7:55-9:30 Working in office (*RF*, *Y*) |
| | 10:30-12:00 Studying at library | 9:45-10:30 Having a meeting at UT (*NonRF*, *N*) | 9:30-10:30 Having a meeting in office (*NonRF*, *N*) |
| | 12:20-13:20 Having a meeting (*NonRF*, *N*) | 10:45-12:00 Working in office (*RF*, *Y*) | 10:30-12:30 Working in office (*RF*, *Y*) |
| | 13:35-14:30 Studying at lab A | 12:20-12:40 Having lunch at downtown | 12:30-14:00 Working in office |
| | 14:30-17:00 Having lab hours (*RF*, *Y*) | 13:00-16:00 Taking a class at UT (*RF*, *N*) | 14:30-15:30 Having a meeting near UT (*NonRF*, *N*) |
| | 17:10-20:00 Studying at Starbucks | 16:30-18:00 Working out at gym (*RF*, *N*) | 15:55-16:30 Working in office |
| | 20:10-20:30 Taking a bus home | 18:00-18:20 Driving car home (*RF*, *N*) | 16:30-17:00 Having a meeting in office (*NonRF*, N) |
| | | | 17:00-19:00 Working in office |
| | | | 19:00-19:30 Driving a car home |

(*RF* and *NonRF* refer to routine fixed activities and non-routine fixed activities. *Y* and *N* refer to activities in which people can and cannot meet with others. Activities without any of the four notations are flexible activities.)

Figure 3.9 shows the analysis results for each pair of these three persons and the visualization provided by this prototype system. The minimum meeting time of 20 minutes excludes time spot meeting opportunities. Because person A can only take a bus and walk, her space-time prisms are not continuous but clustered around two accessible bus stops. In addition, due to the settings of minimum meeting time, maximum travel time, mixed travel modes, and varying travel speeds, the actual space-time prisms look differently from the theoretical shape of two joined cones suggested in time geography. Without phone access, person A and person B only have one potential meeting opportunity (Figure 3.9a2). When person B works in the office in the morning, person A can visit person B since person A knows person B's routine fixed activity and person A has free time in the morning. When they both have access to a mobile phone, Figure 3.9a3 indicates that they do not gain additional F2F potential meeting opportunities with mobile phone access. This example illustrates that improved ICT access does not always guarantee more meeting opportunities due to other constraints on human activities (e.g., one person has flexible time while the other person is engaged in a fixed activity and cannot meet such as the case shown in Figure 3.9a1).

The second example (i.e., meeting opportunities between person A and person C) shows that mobile phone access can relax some spatio-temporal constraints and increase potential F2F meeting opportunities. In this case, person A does not own a car and cannot reach person C's office by bus within person A's two-hour flexible time window in the morning. As a result, it is not possible for person A to meet person C if they do not have phone access. On the other hand, person C knows that person A has lab hours in the afternoon and person C happens to have free time in the afternoon. This generates a potential meeting opportunity for them (Figure 3.9b2). The prototype system reports the number of potential meeting opportunities, the maximum potential meeting time, and the minimum travel time for each potential meeting location. The length of the 3D space-time path segments shown in grey color represents the maximum F2F meeting time window (Figure 3.9b3). Without phone access, the maximum meeting time for this meeting opportunity is 35 minutes, and person C needs to drive 25 minutes to reach the meeting place. With mobile phone access, they can arrange a F2F meeting during their lunch time or after work when they have much free time. The maximum meeting time among these opportunities can increase to one and a half hours, and the total minimum travel time for both of them is only 25 minutes.

The example of person B and person C is an extreme case. They both have high mobility with a car and some free time. Physically they are very close to each other sometimes during the day. Unfortunately, their activity schedules, constrained by their fixed activities, do not fit each other at all. Regardless of their mobile phone accessibility, they do not have any potential F2F meeting opportunities.

The case study demonstrates different effects of mobile phone communication on potential F2F meeting opportunities for individuals. As expected, it could enlarge potential F2F meeting opportunity space, which is consistent with common expectations. The case study also shows that, in some cases, ICT cannot change anything in terms of potential F2F meeting opportunities. In such cases, this study does not suggest that ICT cannot provide convenience for people. People still can call others to plan their F2F meeting opportunities. However, under various constraints, the reality is that sometimes they cannot benefit from telecommunications for F2F meetings. In addition, this study indicates that, in extreme cases, two people who are close to each other in terms of physical distance may not have F2F meeting opportunities. To some extent, it explains why sometimes people choose telecommunication instead of F2F meetings to communicate. Several studies indicate that F2F meetings diminish with an increase in geographical distance between contact members (Boase *et al*., 2006; Tillema *et al*., 2010). However, these studies only consider some static distance variables (e.g., distance between two contacts' homes), leaving out temporal constraints such as the available time windows for meetings, meeting opportunities when people are working outside or during commuting, as well as the spatial context such as feasible meeting locations between two people. The space-time GIS prototype can explore the ignored spatio-temporal context of potential F2F meeting opportunities, which can help us better understand the choice of a communication mode with an objective and holistic perspective.

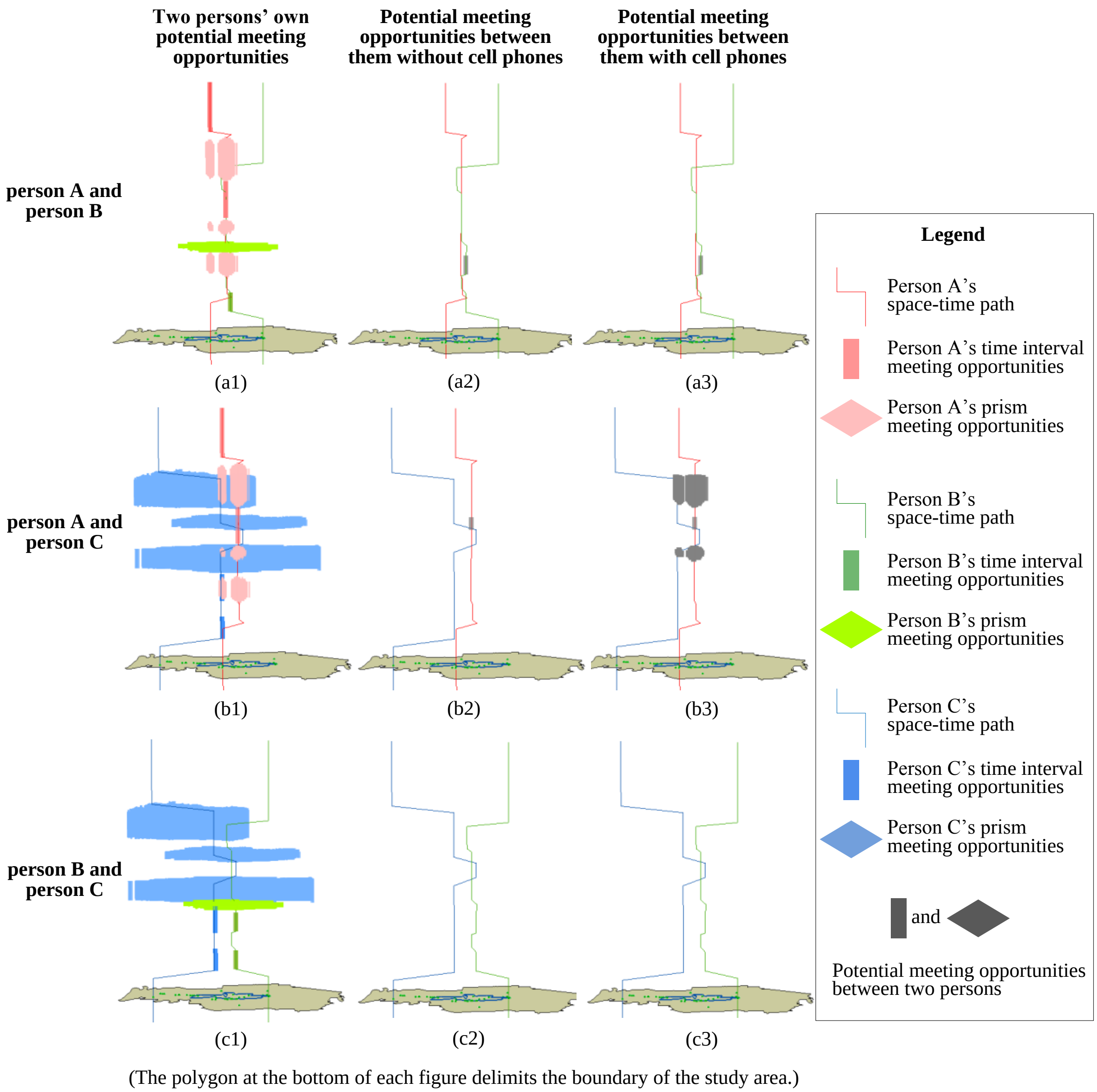



Figure 3.9 The potential F2F meeting opportunities between two persons with and without mobile phones

### *3.3.3 A dynamic scheduling simulation*

Given two persons' travel modes, phone access, routine activities, and actual activities on a particular day (Table 3.3 and

Table 3.4), this case study simulates the changes in potential F2F meeting opportunities over time under four scenarios: (1) neither person has phone access during the day, and person E does not update his plan; (2) both people have access to landline phones, and person E does not update his plan; (3) both persons carry a mobile phone, and person E does not update his plan; (4) both persons carry a mobile phone, and person E updates his plan at 1:00 PM.

In the first scenario without any phone access, the two people only have potential F2F meeting opportunities before 11:50 AM (Figure 3.10). If person D does not go to person E's workplace before 11:50 AM, they will not have any potential F2F meeting opportunities in the rest of the day. If they both can access a landline phone at their workplaces, they can communicate in the morning and meet around lunch time, or contact in the afternoon and meet after work (Figure 3.11). However, if they do not make a call before 12:00 PM, they will lose contact opportunities during the lunch time. Their potential F2F meeting opportunities during lunch time suddenly disappear after 12:00 PM. Similarly, their potential F2F meeting opportunities before going home in the evening disappear after 5:00 PM. Even if they are both shopping downtown, they are not aware of the other's physical proximity without a mobile phone. Compared with the last scenario, a mobile phone brings the two people dynamic arrangement opportunities during their flexible time and while they are traveling outside (see 12:30 PM and 5:50 PM in Figure 3.12). If after lunch person E is certain about the changes in his activities in the afternoon, he is aware of the two free time windows, one before he goes to professor C's meeting and the other after he finishes the meeting. The two people therefore have more meeting opportunities in the afternoon (Figure 3.13).

Table 3.3 Hypothetical routine activities for the two people

| | person D | person E |
|---|---|---|
| Home location | In West Knox | In East Knox |
| Travel mode | Car | Car |
| Phone access | Mobile phone | Mobile phone |
| Activity | 0:00-8:00 Staying at home (*RF*, *N*) | 0:00-8:00 Staying at home (*RF*, *N*) |
| | 8:30-11:00 Working (*RF*, *Y*) | 8:30-12:00 Working (*RF*, *Y*) |
| | 13:00-17:00 Working (*RF*, *Y*) | 13:00-17:00 Working (*RF*, *Y*) |
| | 18:30-24:00 Staying at home (*RF*, *N*) | 18:30-24:00 Staying at home (*RF*, *N*) |

Table 3.4 Hypothetical actual activities for the two people

| person D | person E |
|---|---|
| 0:00-8:00 Staying at home (*RF*, *N*) | 0:00-8:00 Staying at home (*RF*, *N*) |
| 8:27-11:00 Working (*RF*, *Y*) | 8:18-8:30 Working (non-*RF*, *Y*) |
| 11:00-12:00 Working | 8:30-12:00 Working (*RF*, *Y*) |
| 12:13-12:40 Having lunch | 12:10-12:30 Having lunch |
| 12:53-17:00 Working (*RF*, *Y*) | 12:41-13:00 Working at place A |
| 17:15-17:45 Shopping | 13:14-13:40 Staying at friend B's place |
| 18:13-24:00 Staying at home (*RF*, *N*) | 13:52-16:00 Meeting with professor C (non-*RF*, *N*) |
| | 16:18-17:00 Shopping |
| | 17:13-17:40 Shopping |
| | 17:57-24:00 Staying at home (*RF*, *N*) |

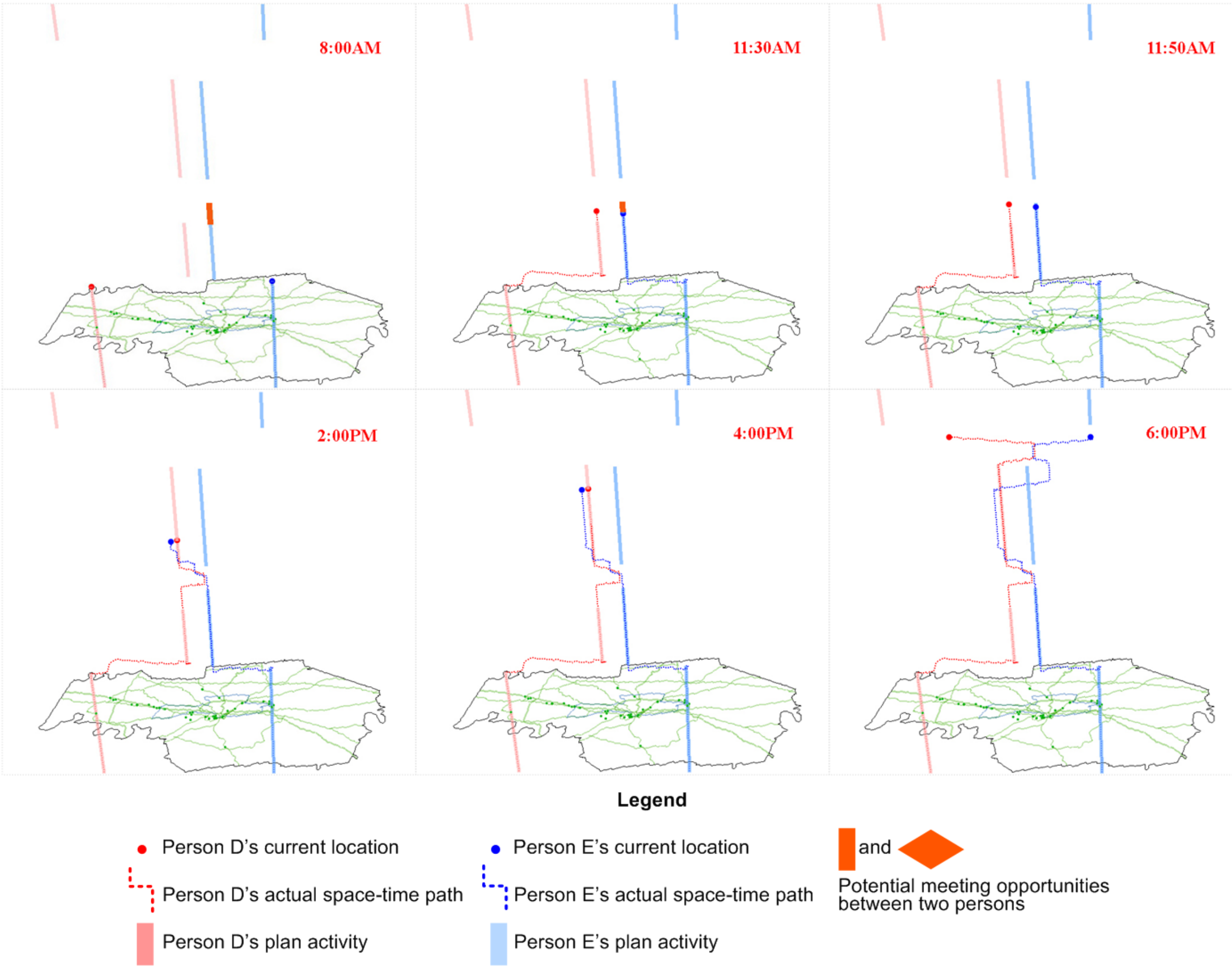



Figure 3.10 The dynamics in potential F2F meeting opportunities over time (no phone access and keep plan)

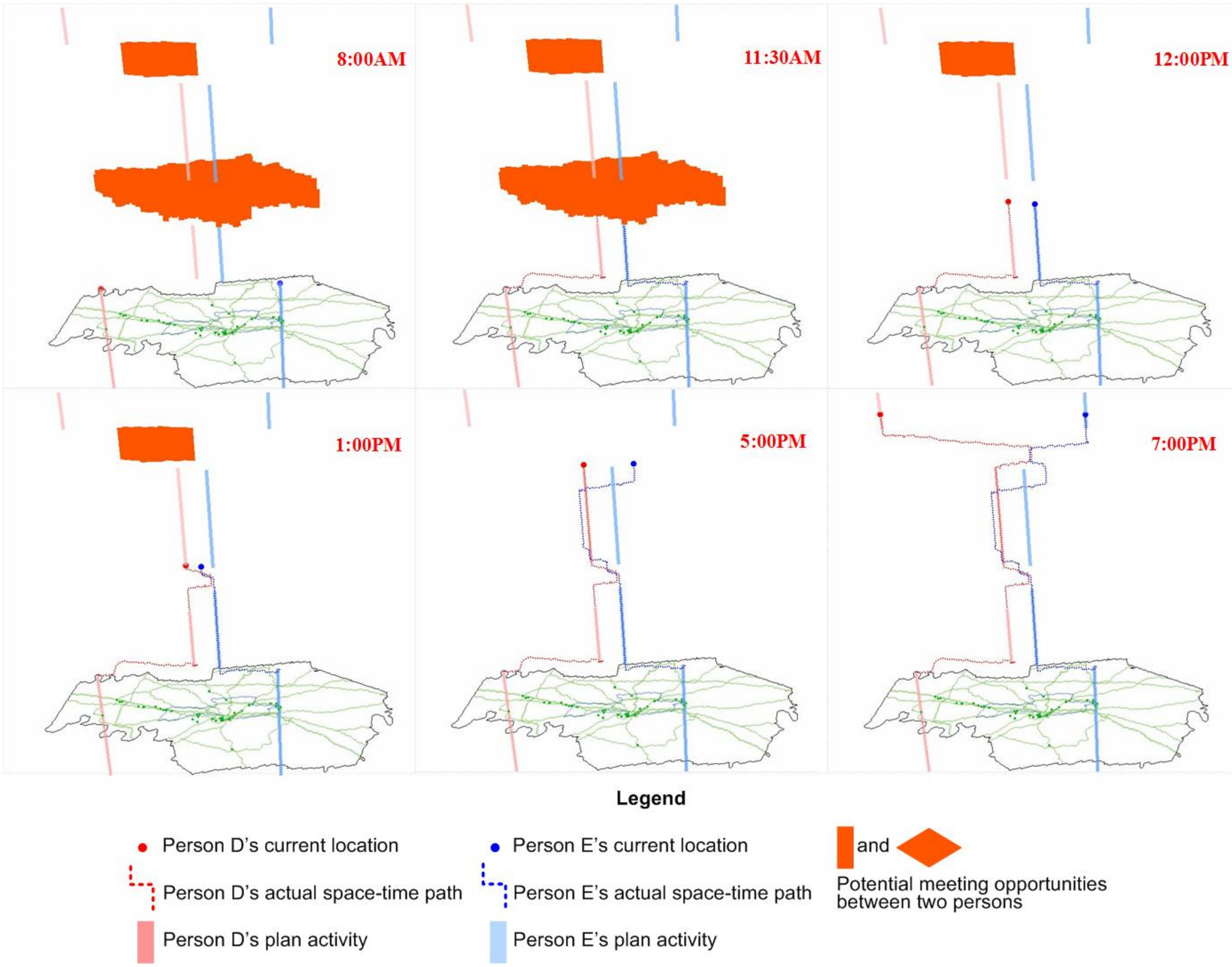



Figure 3.11 The dynamics in potential F2F meeting opportunities over time (landline phone access and keep plan)

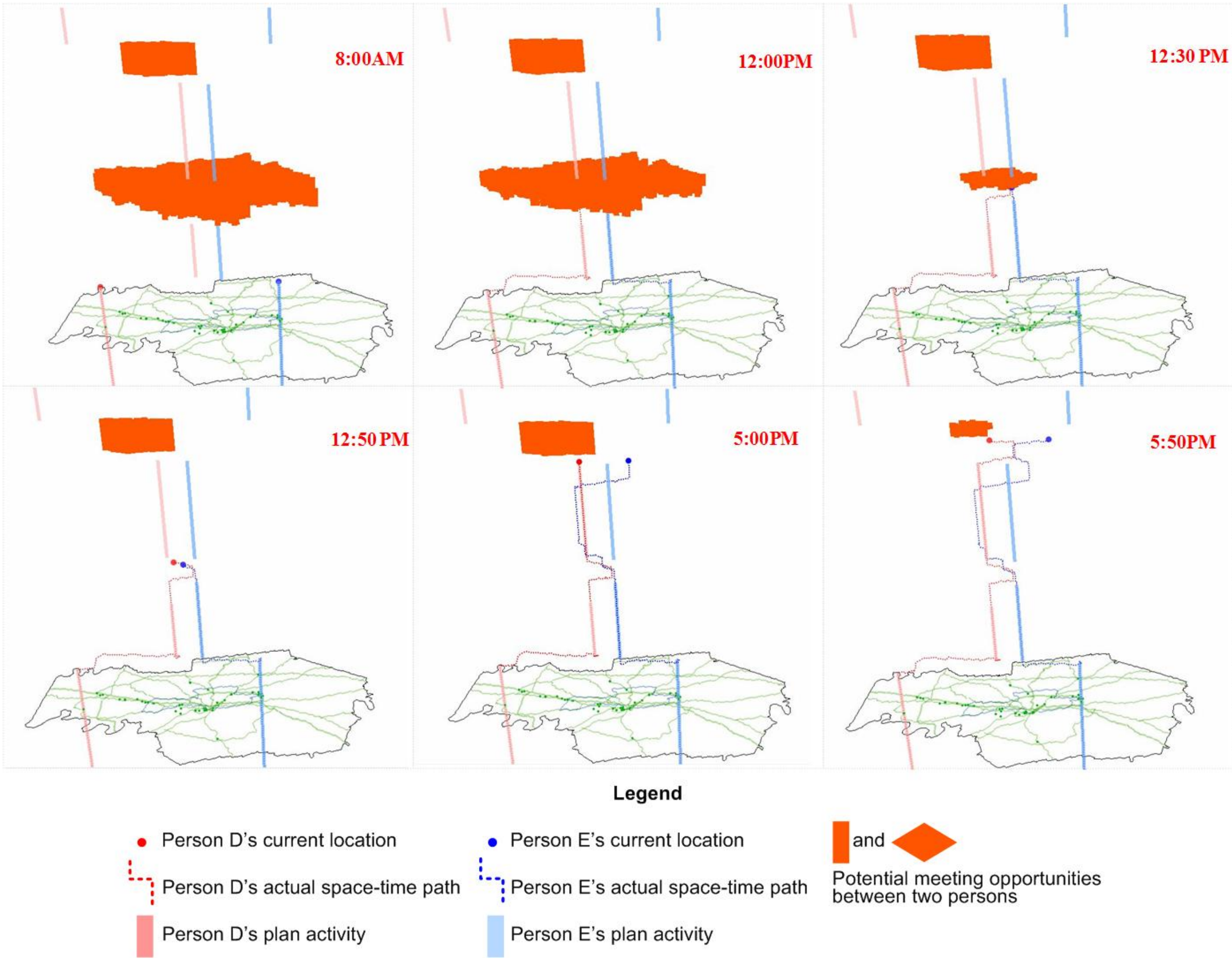



Figure 3.12 The dynamics in potential F2F meeting opportunities over time (cell phone access and keep plan)

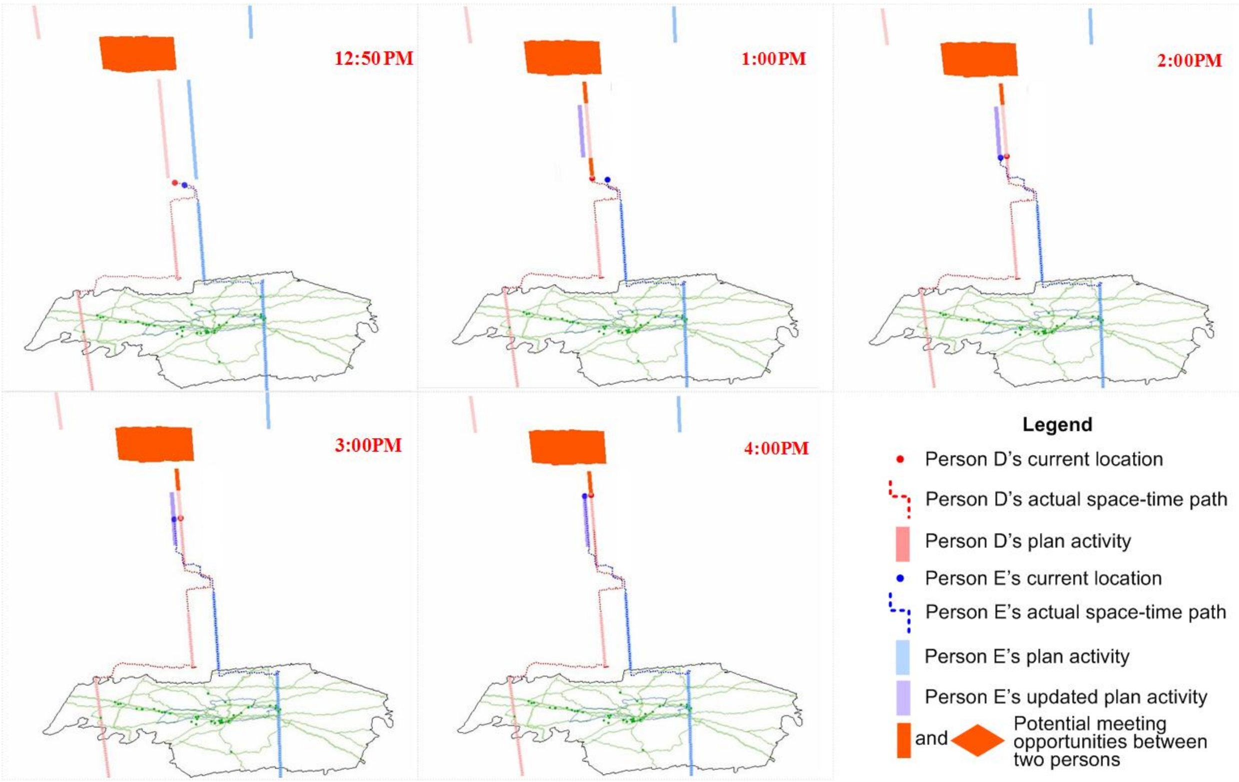



Figure 3.13 The dynamics in potential F2F meeting opportunities over time (cell phone access and update plan)

The dynamic scheduling example indicates the effectiveness of the spatio-temporal exploratory tool in analyzing and visualizing changing interaction opportunities over time. With an analytical perspective, it unveils the process of using telecommunication to arrange and rearrange activities with dynamic activity scheduling.

Through representing potential F2F meeting opportunities in space and time, this prototype system also can suggest potential activity patterns. Taking Person D and Person E as an example, their coupling constraint without phones is significantly stronger than with mobile phones. Those orange 3D space-time prisms in Figure 3.10 (8:00 AM) and in Figure 3.12 (8:00 AM) reveal where they could meet during the day. Given their general activity patterns, if people want to add a F2F meeting, their potential activity patterns will be more limited in space and time without phones compared with having mobile phones. Such explicit spatio-temporal extent for an individual's potential activity patterns could be useful for developing individual accessibility measurements and activity-based models.

## 3.4 Summary

Although a number of studies have been conducted to identify and analyze ICT impacts on individual activities, most of these studies do not offer an analytical framework that can systematically evaluate the interactions between ICT and individual activity constraints in a space-and-time context to help researchers assess the impacts of ICT on individual activities. This study extends the time-geographic analytical framework to quantitatively assess the impacts of phone usage on potential F2F meeting opportunities, as well as their dynamic changes over time. It first defines individual activity types based on their flexibility in space and time, and F2F meeting opportunity types. A dynamic scheduling analysis framework is then developed to capture changing activity plans and changing F2F meeting opportunities over time. To analyze the interactions between phone communication and F2F meeting opportunities, it develops a method to calculate the potential earliest time of finishing a complete phone communication between two people after a given time moment. Since planned activities and meeting opportunities could be updated during a phone communication, it computes the potential F2F meeting opportunity sets before and after the potential earliest complete phone communication separately. These two meeting opportunity sets then form a complete set of all potential F2F meeting opportunities. Moreover, a spatio-temporal exploratory tool is implemented in a space-time GIS. Two case studies based on hypothetical data indicate the effectiveness of the proposed analytical framework and the exploratory tool in discovering and visualizing potential F2F meeting opportunities under different phone access and activity scheduling scenarios.

# CHAPTER 4    HUMAN INTERACTIONS IN VIRTUAL SPACE

Researchers have been studying individual behavior for hundreds of years. These observers have tried to develop frameworks to help explain why a person exhibits particular behavior patterns. These theories are embedded in various disciplines, and one is rooted in geography; time geography builds a framework to examine why an individual exhibits particular movement patterns over space and time (Hägerstrand, 1970).

A human body can exist in only one place in the physical world at any given time. Because of the corporeality of a human body in the physical world, a space-time trajectory can represent a person's movements in physical space over time, and a person's movement pattern in physical space is limited by different constraints, which were summarized by Hägerstrand (1970). However, when our activity space can extend from the physical world to the virtual world, we have to ask, Is there a so-called "movement" for an individual in virtual space? If so, are there any existing theories that also apply to individual movements in virtual space? Are people's movements in virtual space also limited by specific constraints? If so, what are the constraints on people's movements in virtual space? How can we represent, visualize, and analyze people's movements and constraints on human interactions in virtual space?

These questions are not easy to answer, but they are the subject of this and the next chapters. This chapter extends classical time-geographic framework to virtual space. It first presents several ways to define a place, a movement, and a distance in virtual space, and summarizes constraints on individual movements in virtual space. It then presents corresponding ways to define a space-time path in virtual space and extend the definition of a space-time prism from physical space to virtual space. This study implements the presented concepts, as well as exploratory tools based upon these concepts, within a space-time GIS environment. At the same time, with a real dataset, this study demonstrates the effectiveness of the extended framework in exploring human interactions in virtual space.

### 4.1 Basic Analysis Framework

It is possible to explicitly define a geographic place in the physical world with the use of *x*, *y*, and *z* coordinates in a given coordinate system of the earth. Yet, defining a place in virtual space is a challenge. The fundamental characteristics of a geographic place in physical space can be summarized by several common properties: (1) a geographic place is an objective existence, whether one has been there or not, or knows of it or not, it exists on the earth; (2) a geographic place identifies its meaning by its various attached attributes such as a geographic place with a supermarket that offers people an area to buy groceries, or a geographic place in a desert indicates an area that is for the most part inhospitable to humans; (3) geographic places provide containers in which people can conduct physical activities. Of course, these three properties do not cover all common properties of a geographic place, but they can apply to virtual space.

Virtual space exists in a variety of forms, including telephone numbers, webpages, online forums, emails, instant message platforms, social networking services, online games, and so on. It is not easy to locate these forms by coordinate systems, but they do offer tangible containers where people can conduct virtual activities, which could be defined as virtual places. For example, Amazon.com is a virtual shopping location, Netflix.com is a virtual movie theater, and a personal website is a person’s virtual home. They all objectively exist with specific attributes in virtual space, although people usually know of or use only a few of them.

Different virtual forms have their own sense of place and space, which is to say they have their own geography (Batty, 1997). For instance, online shopping websites form a virtual shopping space, online banking websites form a virtual banking space, Flickr forms a photo sharing space, and Facebook and Twitter form different social network spaces. In order to study human interactions in virtual space, this study examined this last category—the virtual spaces created by Social Networking Services (SNS) such as Facebook and Twitter.

For the most part, SNS spaces consist of webpages of individuals and groups. Each Facebook user has a unique webpage, which becomes a virtual place in the SNS space. After logging in, SNS users visit their own webpages, their friends' webpages, post on their own webpages, or comment on their friends' webpages; all of these activities form *virtual movements* in the SNS space. For example, when Nancy posts a new status on her Facebook, she virtually travels to her own place in the SNS space. If she comments about a picture posted on her friend's Facebook album, she virtually travels to her friend's virtual place.

An individual's freedom of movement in an SNS space is limited by various constraints. This study posits two types of constraints on an individual's ability to conduct activities in an SNS space: *access constraints* and *social network constraints*. Access constraints in an SNS space refer to physiological necessities (e.g., sleeping, eating), situation related limitations (e.g., working, in class), and available resources (e.g., Internet access, smart cell phone ownership) that limit virtual activity participation. Thus, access constraints dictate that most people are likely to have more intensive activities in SNS spaces during the day time, people who work are likely to appear in SNS spaces after work, and a person with a smart phone has more access to activities in an SNS space. Social network constraints in an SNS space limit the scope of an individual's movement and reflect rules that limit access to places in an SNS space. For instance, in physical space, the available traffic mode and available time window limit an individual's potential path areas, but in an SNS space, an individual's social networks determine the places that an individual could access. If person A does not know person B's account in an SNS space, person A will not appear in person B's place. Moreover, even if person A knows person B's account, in some SNS spaces such as Facebook, person A cannot visit person B's webpage unless person B permits person A as a friend. This is similar to the authority constraints in the classical time geography.

## 4.2 Virtual Space-time Paths in an SNS Space

A conventional space-time path depicts an individual's movement trajectory in physical space over time. This study defines a *virtual space-time path* as an individual's movement trajectory in an SNS space over time. As the commonly accepted visualization of a space-time path, a 2D space is used to represent an SNS space and a third dimension to represent time. Connecting the virtual places that person A visited will create person A's virtual space-time path (Figure 4.1).

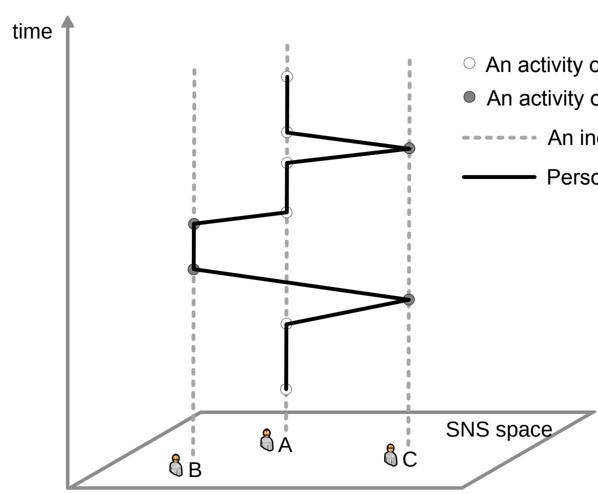
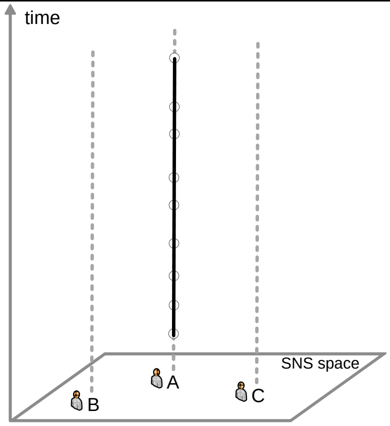
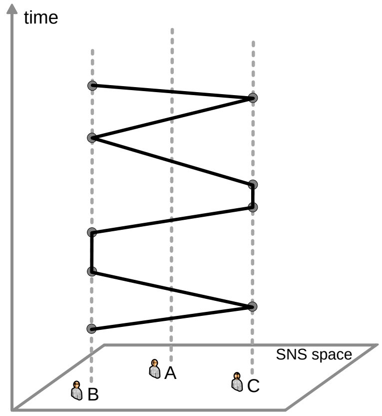
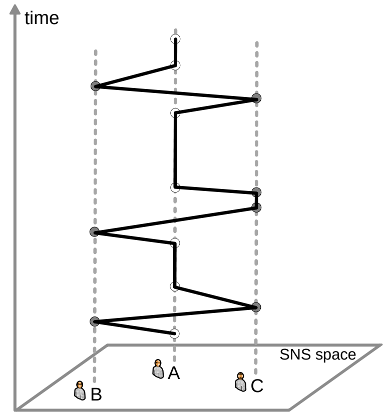
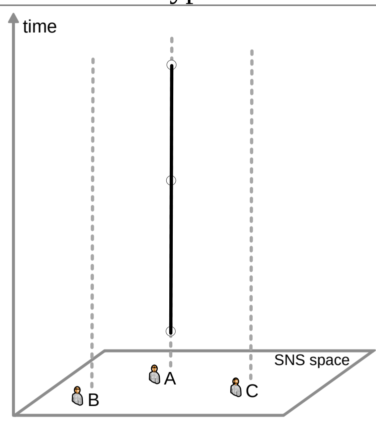
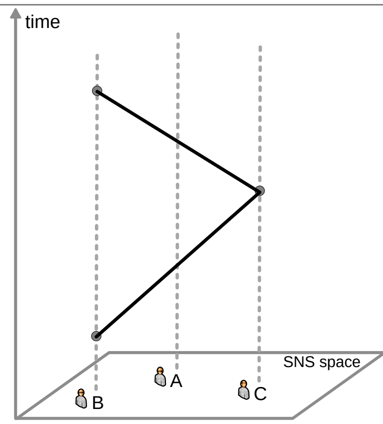
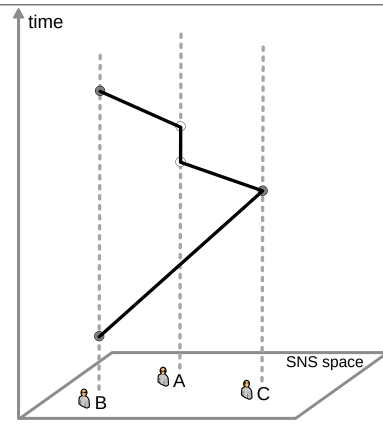



Figure 4.1 A virtual space-time path in an SNS space

Six types of typical virtual space-time paths have been identified (Table 4.1). First, the activity frequency of an individual in an SNS space affects the shape of his/her virtual space-time path. In terms of the activity frequency in an SNS space, SNS users can be divided into active users and non-active users. The two groups are relative to each other, with no fixed boundary between them. Second, the virtual places an individual visits also shape his/her virtual space-time path. One extreme type is that of an individual who only visits his/her own webpage. For instance, some people only write new posts on their own webpages. They may reply to people who comment on their posts, but they never comment on their friends' posts. For such users, their virtual space-time paths likely go along with their virtual places, and sometimes active users and non-active users might have similar virtual space-time paths, shown as Type I and Type IV. The opposite extreme type is the individual who only visits others' webpages; they might be active on their friend's webpages, but they never write on their own. In this case, active users' virtual space-time paths will jump around their friends' places without staying at their own places, exhibited as Type II. If they visit their friends in a relatively fixed sequence, their virtual space-time paths might show some travel patterns, otherwise, the virtual space-time paths are likely to be scattered over space. Non-active users' virtual space-time paths in this case can hardly show patterns, as illustrated by Type V. In reality, the most common type is that of an individual who visits both his/her own and his/her friends' webpages. Active users' own virtual places will be easily identified from their virtual space-time paths, as seen for Type III. Due to low activity frequency, Type VI non-active users' virtual space-time paths in this type scarcely display patterns.

Table 4.1 Six typical movement patterns of virtual space-time paths

| | Only visits his/her own webpage | Only visits others' webpages | Visits all webpages |
|---|---|---|---|
| Active user | <br>Type I | <br>Type II | <br>Type III |
| Non-active user | <br>Type IV | <br>Type V | <br>Type VI |

However, virtual places do not have natural coordinates as physical places. It offers a challenge to mapping virtual places in a 2D space. Since human society entered the ICT era, researchers have been exploring various approaches to mapping virtual spaces and visualizing people's activities in virtual space (Dodge and Kitchin, 2001). In general, researchers represent virtual places by the geographical locations of service providers or users (e.g., server locations, an Internet user's geographical location), the topology of their connections (e.g., topological structure of websites, social network graphs), or geographical locations in the virtual reality environment. Virtual reality environment is not relevant to this study, so only the first two approaches to visualize virtual space-time paths in an SNS space are undertaken here.

### *4.2.1 Virtual space-time paths based on geographical locations*

Focusing on human interactions, this study first chose an SNS user's geographical location to represent his/her virtual location. If using an individual's geographical location as his/her virtual location, as he/she moves in the physical world, his/her virtual place will accordingly move (Figure 4.2). Thus, an individual's virtual space-time path moves across geographical space; it projects people's virtual movements onto the earth. When a person visits the Facebook page of a friend who lives on the other side of the earth, he/she travels the equivalent of half the earth in the physical world. Being represented by geographical locations, virtual places have their unique coordinates on a map, and the distance between two virtual places demonstrates the geographical distance between the two associated persons.

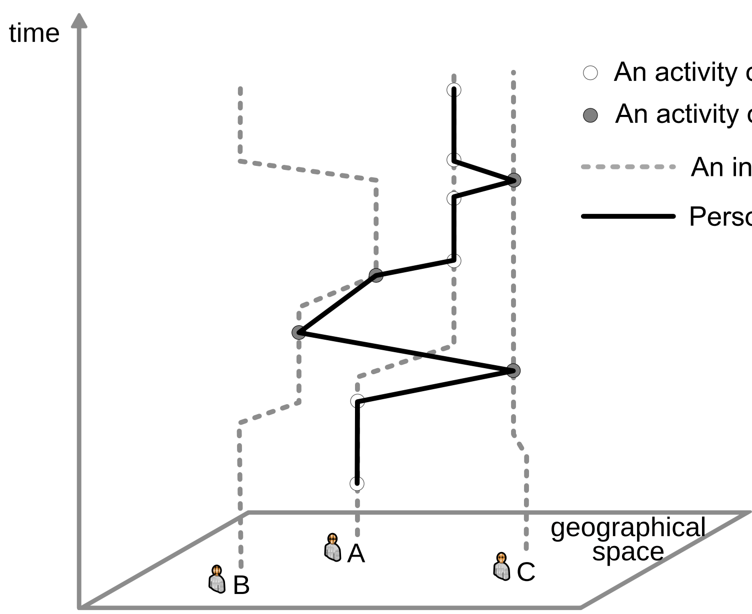



Figure 4.2 A virtual space-time path in an SNS space based on geographical locations

### *4.2.2 Virtual space-time paths based on social network graph*

As discussed in Chapter 2, in terms of a social network graph, Euclidean distance-based graphs contain more meaning about relations between people compared with topological distance-based graphs. Euclidean distance-based graphs are closer to geographical maps. Therefore, this study chose Euclidean distance-based graphs to map people's virtual places in an SNS space. People move their virtual places in an SNS space over time in the same way that they move their homes in the physical world. For example, person A, person B, and person C are friends on Facebook (Figure 4.3). At moment *t1*, communication on Facebook between person A and person C is more than communication between person A and person B. At the meantime, person B and person C are not as close to one another as they are with person A. The Euclidean distance-based graph is shown by the layout at moment *t1*. In the next few days, person A talks more with person B than before on Facebook. Their relative locations at moment *t2* change accordingly. Then person A communicates with person B even more, and person B and person C also increase their communication, which forms the layout of their virtual locations at moment *t3*. During this process these three persons move closer overall, and person A moves his/her virtual place from a location closer to person C to a location closer to person B. This study defines the path connecting an individual's moving virtual places in an SNS space over time as a *social space-time path*. A social space-time path reveals the trajectory of an individual's relative position within a social network over time.

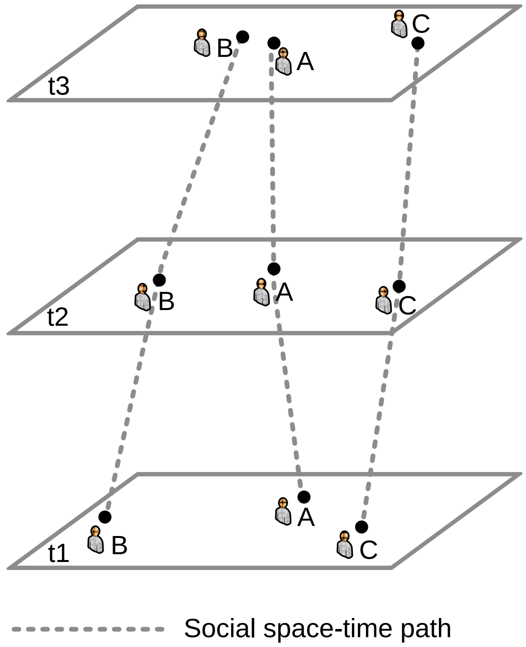



Figure 4.3 Social space-time paths in an SNS space

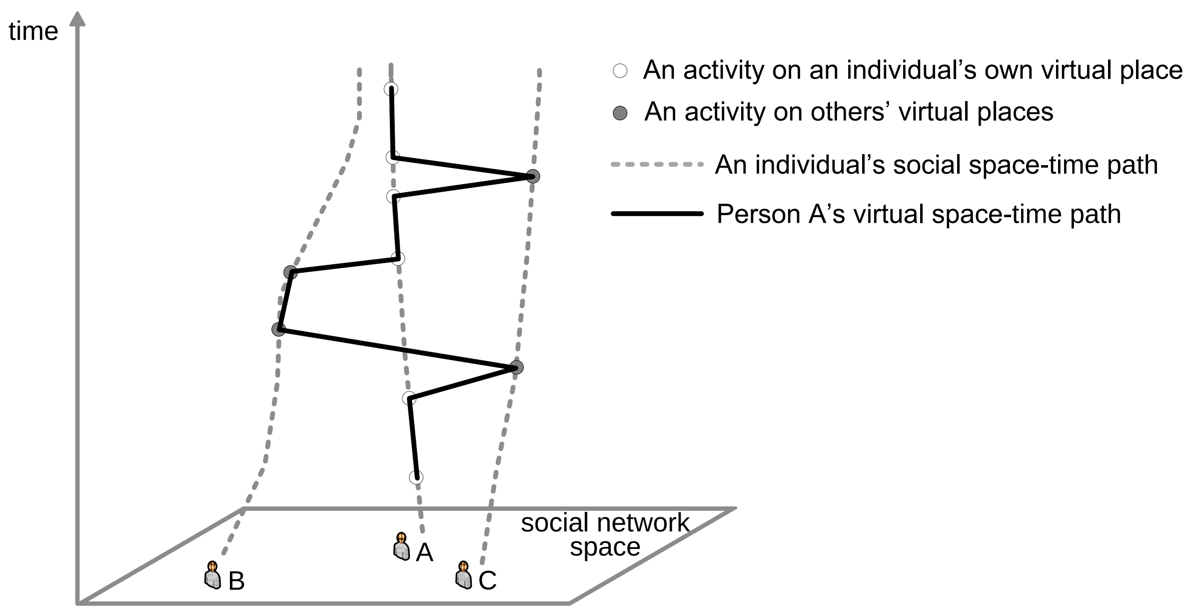



Figure 4.4 A virtual space-time path in an SNS space based on social network graph

Similar to the way a virtual space-time path is created based on physical space-time paths (Figure 4.2), a virtual space-time path is created based on social space-time paths (Figure 4.4).

Person A's virtual space-time path is created by connecting stops that person A had both on his/her own and others' social space-time paths along with time stamps.

### *4.2.3 Social space-time paths in an SNS space*

Social space-time path is a novel concept; this section discusses creating a social space-time path. Technically, as long as a time interval is chosen and data is available, multidimensional scaling (MDS) procedures can produce a static Euclidean distance-based social network graph for each time interval (see MDS discussion in Section 2.4.1). Then, as long as each individual's ID is kept in the output of MDS, a social space-time path can be created for each individual (Figure 4.3). However, in practice, a common problem occurs in dynamic social network visualizations, which is layout instability (Leydesdorff *et al.*, 2008). In a simple example, Figure 4.5a represents three people's social space-time paths created by three static Euclidean distance-based social network graphs. It is easy to interpret the dynamic relationships among the three people from this visualization. However, the output layouts of MDS have some degree of uncertainty. With a particular loss function, the initial seed of an MDS procedure will affect the output layout. In most MDS programs, the initial seed could be a random layout or a fixed layout provided by users. A fixed layout seed usually keeps more stability in a series of results than a random layout seed. Nevertheless, even if all parameters of MDS programs were controlled to maintain more stability in a series of results, rotational dispersion of a layout would still occur. Figure 4.5c and d are both the output layouts of MDS for the three people at moment *t*2. The three people's relative positions are the same in the two layouts, except one is the other's layout rotated by 180 degrees. MDS programs do not distinguish these two layouts. If the layout in Figure 4.5d is used in this example, the social space-time paths of person A and person B will intertwine with each other as shown by Figure 4.5b. Obviously, Figure 4.5b is not as easy as Figure 4.5a for researchers to interpret. Therefore, a rotation procedure is necessary to create social space-time paths as stable as possible. The rotation procedure is discussed in detail in the case study section.

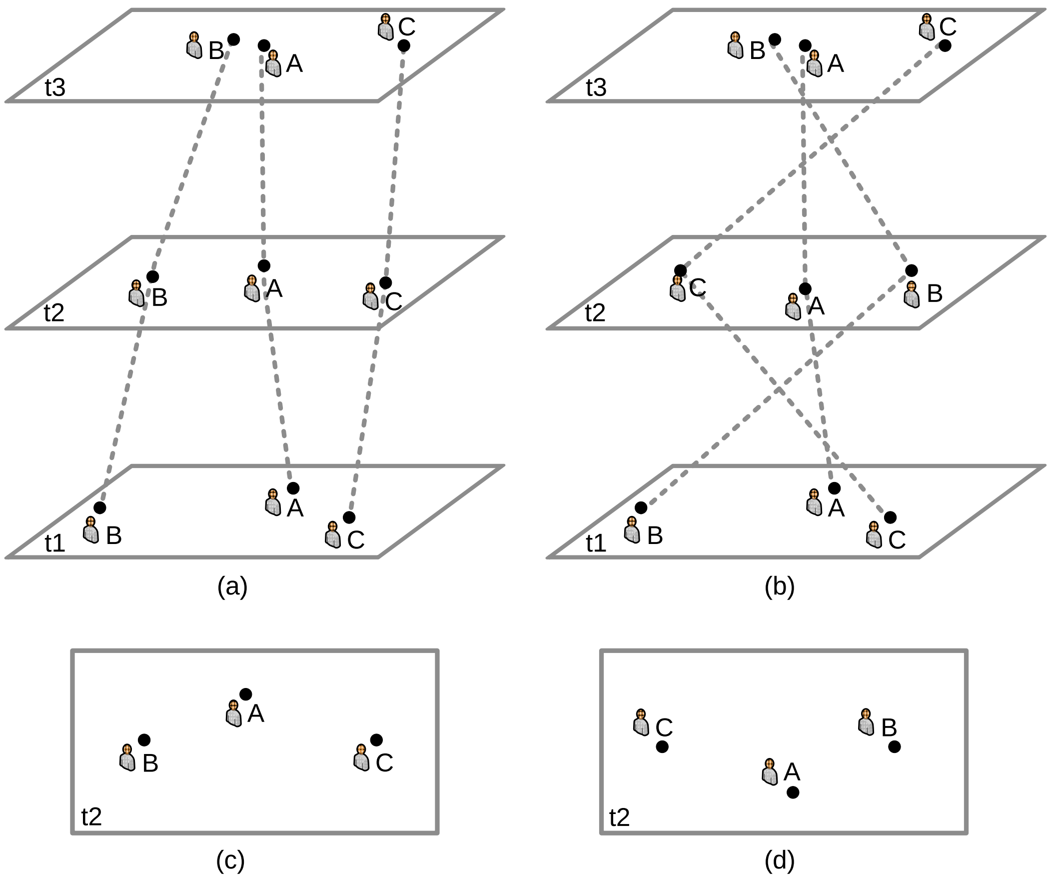



Figure 4.5 The problem of layout instability

## 4.3 Virtual Space-time Prisms in an SNS Space

A space-time prism in the physical world depicts the space-time possibilities of an individual trajectory in geographical space under a set of constraints. In other words, a space-time prism should disclose the places that an individual can potentially reach and the time windows in which he/she can potentially stay at these accessible places. Using the same definition, an individual's *virtual space-time prism* should be able to describe the virtual places that this person could potentially access and the time windows in which this person could potentially appear at these virtual places.

Based upon access and social network constraints in an SNS space, a virtual space-time prism is measurable. For instance, one day person A can access the Internet during the time windows $T_1$ and $T_2$, which become the potential time periods during which he/she can access an SNS space (Figure 4.6). In the SNS space, person C, person D, and person E are person A's friends. Due to the friend permission settings in the SNS space, the potential virtual places that person A could reach would include his/her three friends' webpages, as well as his/her own webpage. The space-time possibilities that person A can access in the SNS space form person A's virtual space-time prisms (represented by grey solid bars). On the same day, person B can get on the SNS space during the time window $T_3$. Person C, person D, and person F are person B's friends in the SNS space. As a result, the space-time possibilities (represented by oblique line bars) become person B's virtual space-time prisms.

In the same way that intersections of peoples' space-time prisms in the physical world depict their potential face-to-face meeting opportunities, the intersections of virtual space-time prisms of different people show the potential opportunities for their synchronous presence in virtual space, such as sending instant messages or chatting on someone's webpages. In the example above, although person A and person B are not friends in the SNS space, they could possibly meet on webpages of their common friends, person C and person D, during the overlapped time window of $T_2$ and $T_3$ (two grey oblique line bars).

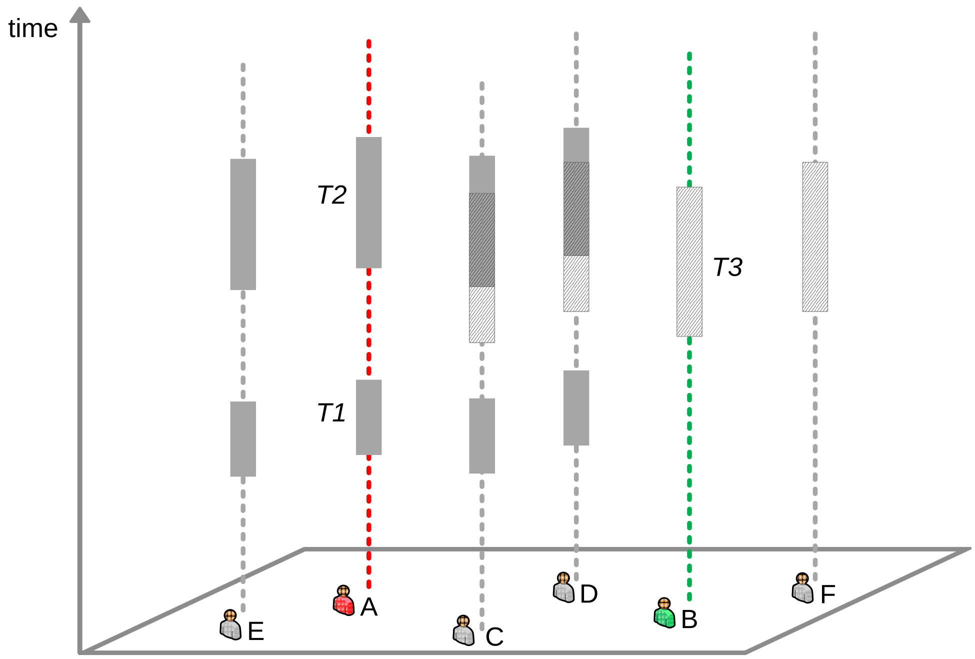



Figure 4.6 An example of virtual space-time prisms

If the activity history of a group of people's in an SNS space is available, the virtual space-time prism of one group member can not only depict the space-time possibilities of his/her movements in an SNS space, but can also reveal the probabilities of him/her being in a particular virtual place during a particular time window. Based on person $A$'s activity history in an SNS space during the time period $\tau$ (e.g., one month, one year), the probability of person $A$ being in his/her friend $F_i$'s virtual place within a particular time window $T_k$ (e.g., 2:00 PM – 3:00 PM on Monday) is:

$$P(A \rightarrow F_i)_{T_k} = P(A \rightarrow F_i)_\tau \times P(A | T_k)_\tau \tag{4-1}$$

where $P(A \to F_i)_\tau$ is the probability that person *A* visits friend $F_i$'s virtual place, which is obtained from person *A*'s activities in an SNS space during the time period $\tau$ ; $P(A|T_k)_\tau$ is the probability that person *A* enters an SNS space within the time window $T_k$ , which is obtained from person *A*'s activities in an SNS space during the time period $\tau$ .

$$P(A \to F_i)_\tau = \frac{C(A \to F_i)_\tau}{\sum_{i=1}^{n} C(A \to F_i)_\tau} \tag{4-2}$$

where $C(A \to F_i)_\tau$ is the total count of times that person *A* visits friend $F_i$'s virtual place during thetime period $\tau$ and $n$ is the total number of person *A*'s friends in an SNS space.

$$P(A|T_k) = \frac{C(A|T_k)_\tau}{C(T_k)_\tau} \tag{4-3}$$

$C(A|T_k)_\tau$ is the total count of times that person *A* enters an SNS space within the time window $T_k$ during the time period $\tau$ and $C(T_k)_\tau$ is the total count of the time window $T_k$ during the time period $\tau$ .

Assuming the independency of events, the probability of synchronous presence at the common friend $F_i$'s virtual place for person *A* and person *B* is:

$$P(A \cap B)_{T_k} = P(A \to F_i)_{T_k} \times P(B \to F_i)_{T_k} \tag{4-4}$$

where $P(B \to F_i)_\tau$ is the probability that person *B* visits friend $F_i$'s virtual place, which is obtained from person *B*'s activities in an SNS space during the time period $\tau$ .

Given the probabilities of an individual visiting his/her friends' virtual places, probabilistic virtual space-time prisms can be created to explore an individual's virtual trajectory and synchronous communication possibilities among people at a more meaningful perspective.

This chapter has discussed concepts of virtual places, virtual movements, and constraints on virtual activities, virtual space-time paths based on two types of virtual place layout, social space-time paths, virtual space-time prisms, and probabilistic virtual space-time prisms. The following sections present a case study to implement the presented concepts and discuss their advantages and limitations.

## 4.4 Data Collection and Preparation

### *4.4.1 Data collection*

The main goal of data collection is to amass the activity history of a group of connected people in an SNS space. This study chose a group of the author's classmates at Nanjing University in China as subjects. The author entered the Department of Geography at Nanjing University in 1999 for a B.S. degree, and graduated in 2006 with a M.S. degree. Her social network mainly consists of people who entered the Department of Geography between 1998 and 2004 and who graduated between 2003 and 2008. The author first identified 44 potential participants through her own social network. The potential participants were selected because they have been active on social networking websites in order to maintain connections with other classmates after graduation.

The author contacted each potential participant, and invited him/her to participate in this study. The author used different ways to contact participants, including contacts by telephone, e-mail, and social networking websites. As a result, 37 of the 44 potential participants agreed to join this study.

The data collected consists of three parts: online communications data, history of residences, and ICT habits in maintaining social networks. Social networking websites became popular among Nanjing University students after 2003, and most of the potential participants graduated after 2004, so the time span of the survey was set from Jan 1, 2005 to Nov 30, 2010. Online communications data on many social network websites are publicly available for connected friends; thus, it was feasible to collect message records from these social networking websites. The major social networking websites used by the selected group included Lily BBS (the bulletin board system of Nanjing University), Kaixin website (an equivalent social networking website of Facebook in China), and Facebook. The three SNS spaces together formed a relatively complete SNS space for the participants.

The selected group used Lily BBS as their major social networking website from 2005 to 2008. Lily BBS has a blog system in which each user can maintain a blog space. Users post their blogs there, and blogs marked “public” are publicly available for all Lily BBS users. Any Lily BBS user can make comments in public blogs (Appendix A). Lily BBS is an SNS space that does not have friend permission settings; however, a user must know other users’ unique account names to find their webpages, which limits activities in this SNS space. The author obtained all participants’ user account names and developed a computer program that routinely visited each participant’s public blog. The program recorded when a participant posted a blog, which participants made comments, and when the comments were made.

The Kaixin website, which is quite similar to Facebook, was launched in China in 2008. Some of the potential participants moved their communication platform from Lily BBS to Kaixin website. Like Facebook, user webpages on Kaixin are controlled by privacy settings. Since the author of this study was a friend of all potential participants, she was able to visit each participant’s webpage. In the same way as for Lily BBS, she developed a computer program to automatically download and record activity on the site, such as when a participant posted new status/event/diary/picture entries, which participants made a comments, and when those comments were made (Appendix A).

Some of the participants who had been studying or working in other countries also used Facebook. The author developed another computer program capable of visiting each participant's Facebook page and recording participants' status/event/diary/picture entries, the comments of participants, and when the comments were posted (Appendix A).

One thing to be aware of is that only visits with a post or a comment on the three selected SNS websites can be accessed. The times when a user logged in and logged off a website and the visits when a user does not leave any messages on a webpage are not publically accessible on the websites. No communication contents were kept in order to protect the privacy of the participants. The database only maintained records of participants. Communication records of other users who also made comments on a participant's webpage were excluded.

For the other two components of the data collection, the author asked participants to complete a survey that asked about their residences during the previous five years and their use of ICT to maintain connections with their classmates. The author used SurveyMonkey.com to create an online survey, sent the link to each participant by e-mail, and downloaded the responses from SurveyMonkey.com after the completion of the online survey (Appendix B). The survey was administered in both English and Chinese. The author added an "informed consent" page as the first page of the online survey; participants could only contine the survey by checking the "agree" checkbox.

### *4.4.2 Database design*

Data from the 37 participants were organized in a personal geodatabase in ArcGIS 9.3 (Figure 4.7). There are three major tables (table format in geodatabase) in the database: *Individual information table* stores each participant's unique ID, pseudonym, gender, age, major at Nanjing University, place of residence on Jan 1, 2005 and on Nov 30, 2010.

*Virtual communication table* stores 24,765 publically accessible communication records among the participants. Each communication record includes the visitor's unique ID, the visited person's unique ID, date and time of the visit, visit type, unique conversation ID, and SNS platform (Table 4.2). For example, person "20101" posted a diary on his/her Kaixin page on the morning of Oct 20, 2009. Posting a new status/event/diary/picture on a person's own webpage is marked as the type of activity "Post" in the database. A "Post" activity always has the same visitor ID and visited ID, and starts a new conversation. Later his/her friends "20105" and "20107" commented on the diary around noon. Commenting on a friend's webpage is marked as the activity type "Comment" in the database. A "Comment" activity always has a different visitor ID and visited ID. In the afternoon, person "20101" wrote in his/her own diary's comment area. Without investigating the comment content, it is impossible to identify who person "20101" talked with. The activity of commenting on a person's own webpage is designated "Reply" without identifying the target person. A "Reply" activity also has the same visitor ID and visited ID. Moreover, all visit times in the virtual communication table are stored both in US Eastern Time and the visitor's local time.

Table 4.2 Three types of communication records in an SNS space

| Visitor ID | Visited ID | Visit time (local time) | Visit type | Conversation ID | SNS |
|---|---|---|---|---|---|
| 20101 | 20101 | 10/20/2009 8:56:00 AM | Post | 20101_diary_1 | Kaixin |
| 20105 | 20101 | 10/20/2009 11:43:05 AM | Comment | 20101_diary_1 | Kaixin |
| 20107 | 20101 | 10/20/2009 12:03:22 PM | Comment | 20101_diary_1 | Kaixin |
| 20101 | 20101 | 10/20/2009 4:35:52 PM | Reply | 20101_diary_1 | Kaixin |

*Physical migration table* stores 120 migration events reported by participants. Each migration record includes a participant's unique ID, the unique ID of the destination, and the date of the move. Each destination place is associated with a place feature stored in the place feature class (point feature class in geodatabase). The attributes of a place feature include a unique ID indicating in which city, region, country, and continent it is located, and its time zone code. To protect participants' privacy, all residency places were collected at city level. The concrete $x$ and $y$ coordinates of a residency place are randomly assigned within the city area (Figure 4.8).

Moreover, each individual associates with a physical space-time path, a virtual space-time path, and a social space-time path.

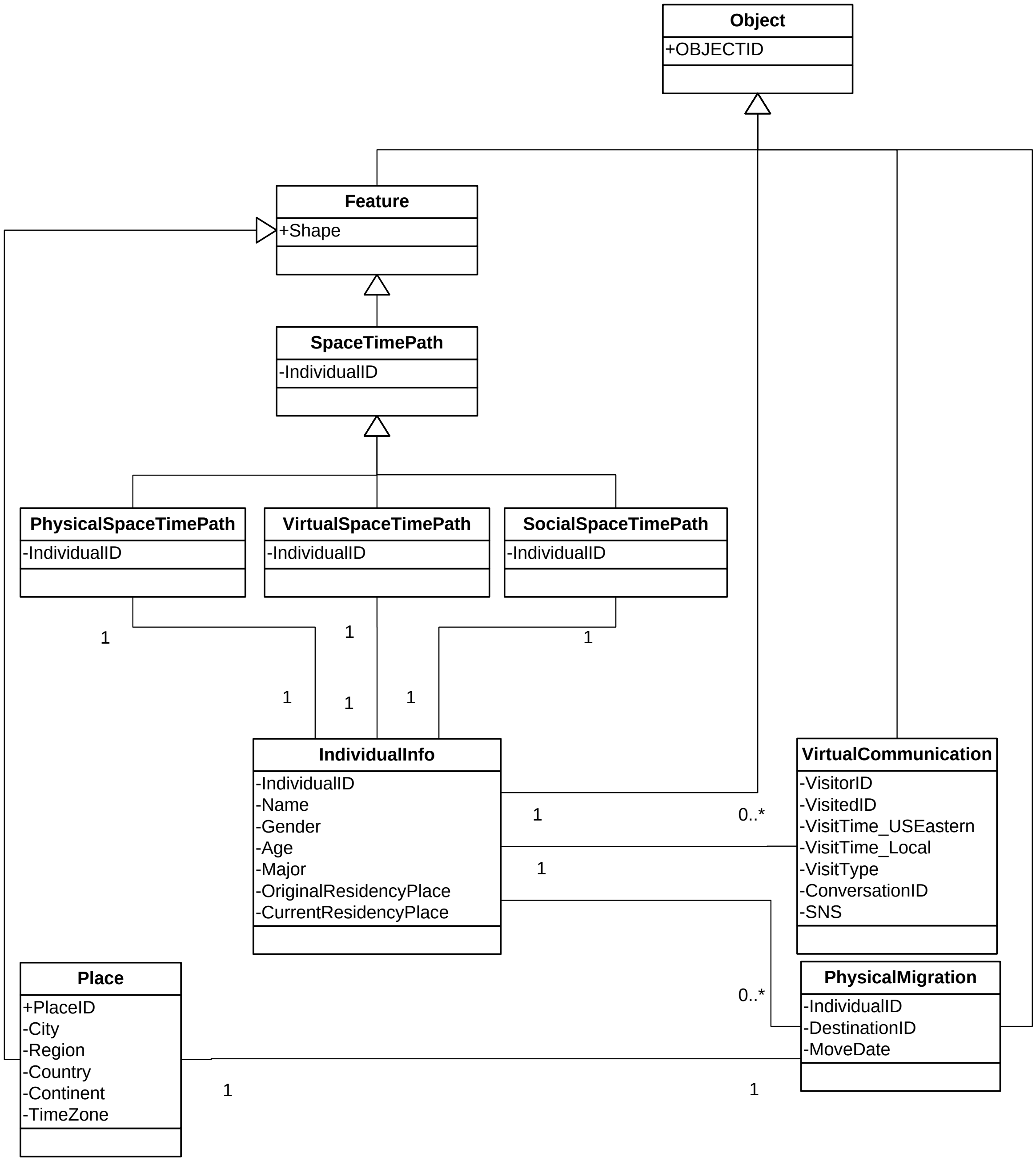



Figure 4.7 UML diagram of the geodatabase


(Map projection: World Mercator. This map does not include Antarctica.)

Figure 4.8 Places of residence of participants in the last six years

## 4.5 Case Study and a Space-time GIS

### *4.5.1 Physical space-time paths*

Figure 4.9a shows all participants' physical space-time paths based on a world map with a World_Mercator projection in ArcScene. The highlighted areas correspond to the countries they have ever been in the past six years. Most of the study participants changed their residency places after graduation: 14 have been studying or working abroad; of these, 9 are still living abroad (Figure 4.9c), while 5 have already returned to China (Figure 4.9d). The other 23 participants moved their residency places only within China (Figure 4.9b), and 5 of them never moved out of Nanjing City after graduation.

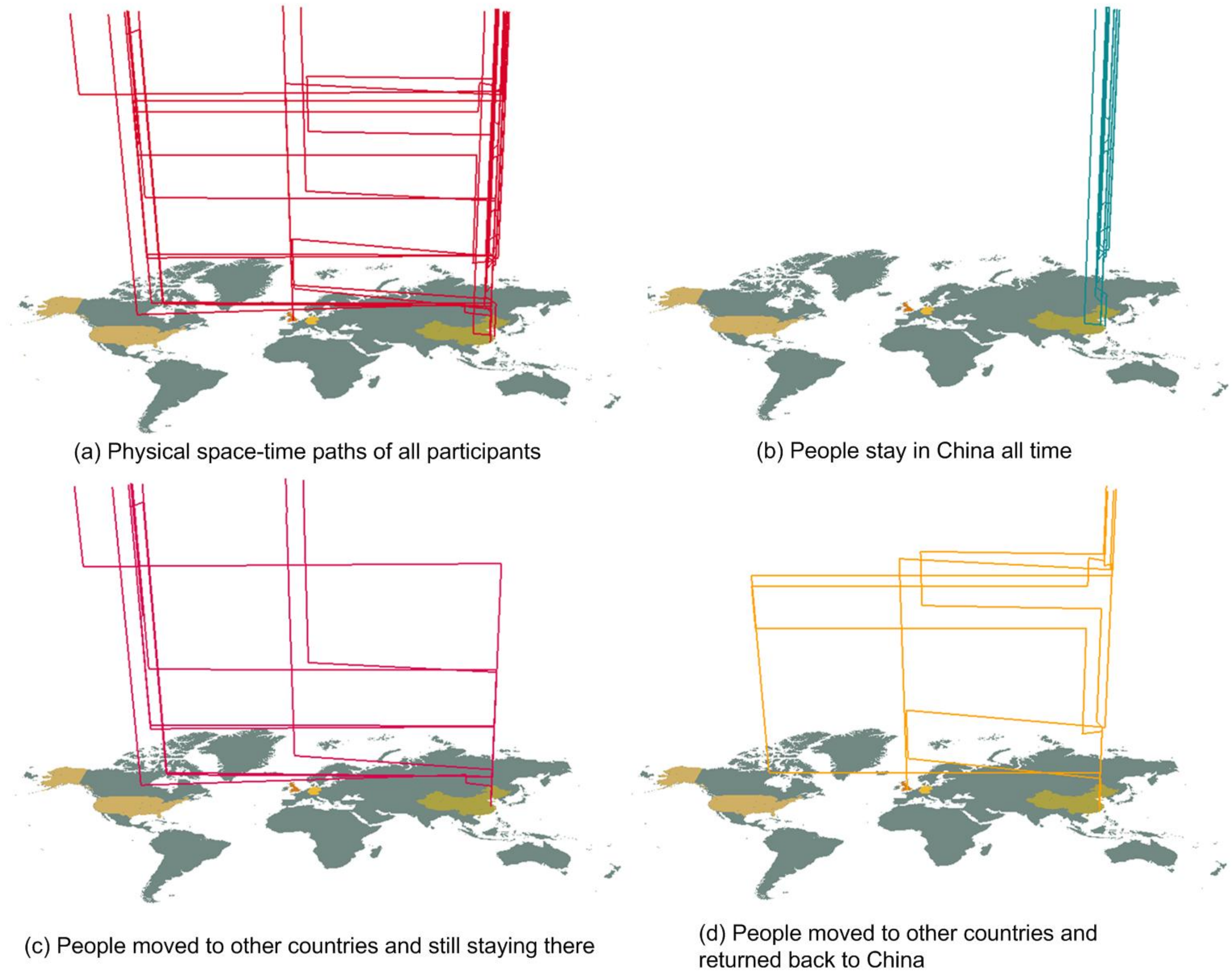



Figure 4.9 Physical space-time paths of participants

### *4.5.2 Virtual space-time paths based on physical space-time paths*

As this study has hypothesized, one representation of a virtual space-time path is based on physical space-time paths and virtual communication records. The spatial-temporal resolution of individual tracking data determines the shape of a physical space-time path. In this study, participants' tracking data at a GPS level was not available, nor were short trips such as out-of-town trips for business or pleasure. The physical movement data that can be collected without burdening participants is the history of their residences at the city level. The relatively long temporal span of this study—almost six years--means that the resolution of the migration data is reasonable.

A function to create virtual space-time paths as described above was developed under the VBA environment in ArcScene 9.3 (Figure 4.10). The inputs of the function include the physical space-time paths based on the physical migration, virtual communication, and individual information tables. This function created all participants' virtual space-time paths based on their physical space-time paths.

Guia moved from China to the U.S. around June 2005 and was still in the U.S. in December 2010 (all names appearing in this study are pseudonyms). Figure 4.11a shows Guia's virtual space-time path based on physical space-time paths. From different angles, Figure 4.11b and Figure 4.11c show Guia's migration pattern (red dotted line) and her friends' migration patterns (green dotted lines). In this study, users who have at least one activity per month in average during a period were defined as *active users* in the period; otherwise, they are *non-active users* in this period. In general, Guia was a stable Type III active user in the SNS space over the past six years (Table 4.1).

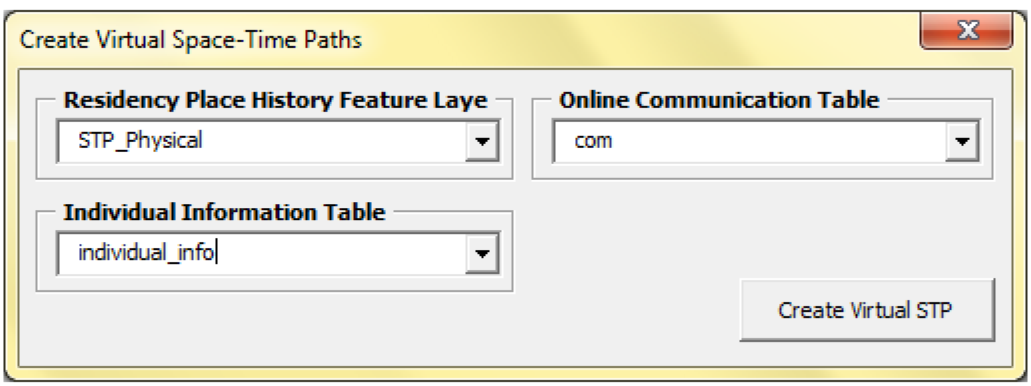
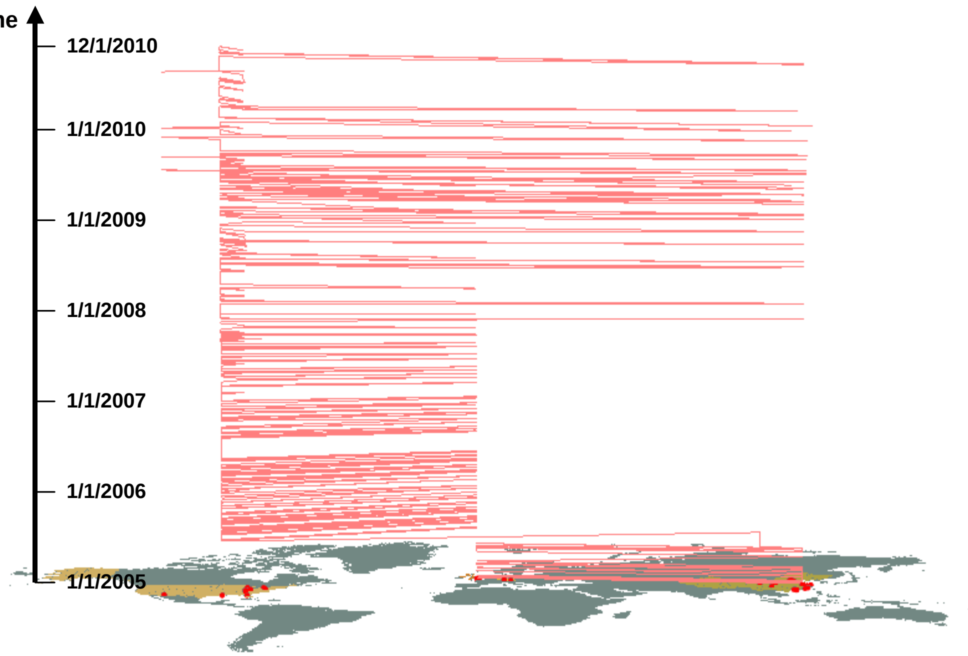


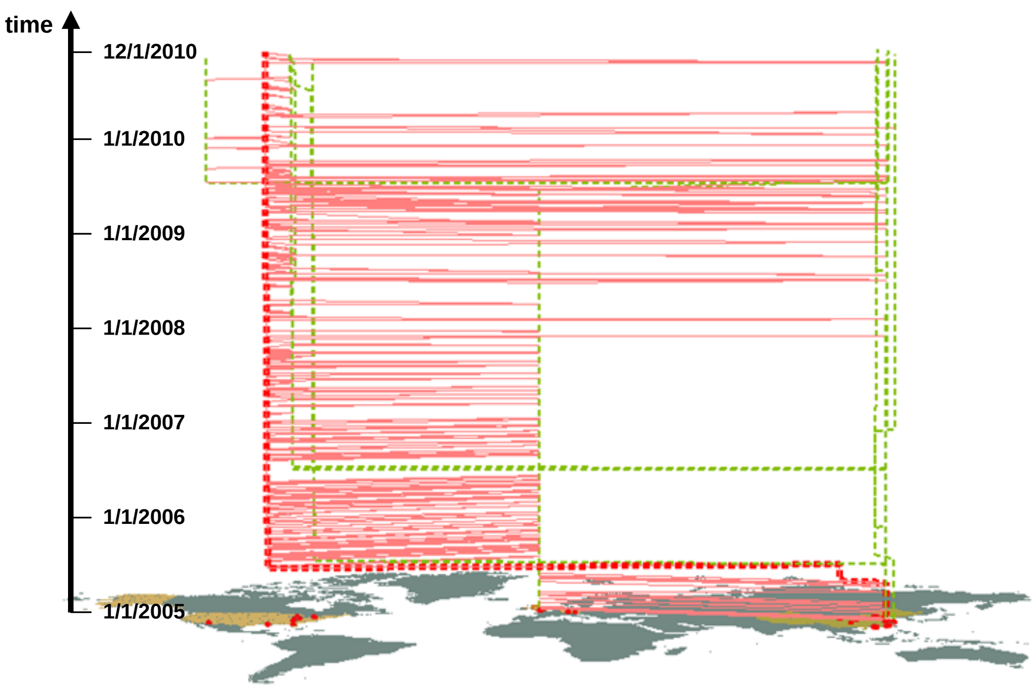

Figure 4.10 The function to create virtual space-time paths in ArcScene

Before 2008, most of her visits in SNS space concentrated on a friend who lived in Europe, and she never commented on the webpages of friends in China. After 2008, she began to communicate with friends in China and had regular communication with friends in the U.S. The changes in 2008 probably are due to the transfer of her SNS platform; before 2008, the participants used Lily BBS as their SNS platform. After 2008, Kaixin, one SNS equivalent to Facebook in China, gradually replaced Lily BBS for most of the participants. Within a blog system, people usually only regularly communicate with their close friends in that system. Just as on Facebook, people on Kaixin are triggered by the friendly design of common communication means to talk with more friends. Moreover, the friend who lived in Europe for a few years had a unique role within Guia's social network in the SNS space. This friend, Nina, stayed in Europe until July 2009. At that time she moved back to China (Figure 4.11b and Figure 4.11c). Figure 4.11d displays a special angle for looking at Guia's visits to Nina's place. Guia kept visiting Nina's place regularly in the first five years.

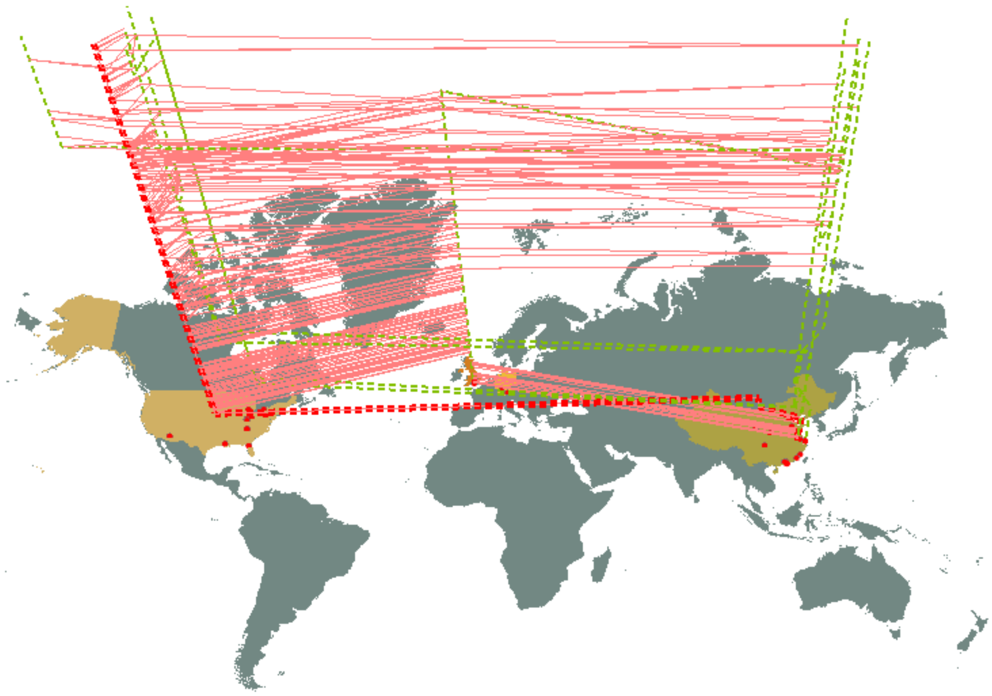
In the sixth year, the frequency of Guia's visits dropped sharply. This pattern does not necessarily mean that Guia paid less attention to Nina in the SNS space during this year. An individual's virtual place is different from a public place in the physical world. A brick-and-mortar store might have customers coming continuously as long as it runs normally. However, people go to their friends' virtual places largely prompted by new posts by those friends. Figure 4.11d also shows the frequency of Nina's new posts over the past six years. Nina's new post frequency largely matches Guia's visit frequency at Nina's place, which implies a reason that shapes Guia's virtual space-time path.



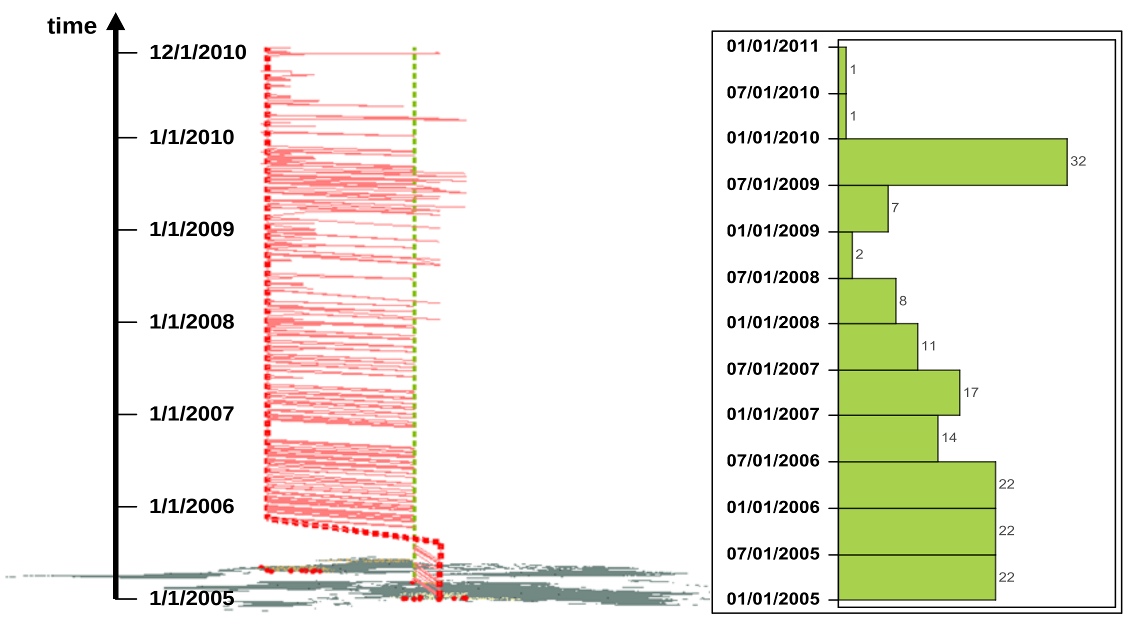

(a) Guia's virtual space-time path based on physical space-time paths




(b) Guia's virtual space-time path, her physical space-time path, and her visited friends' physical space-time paths



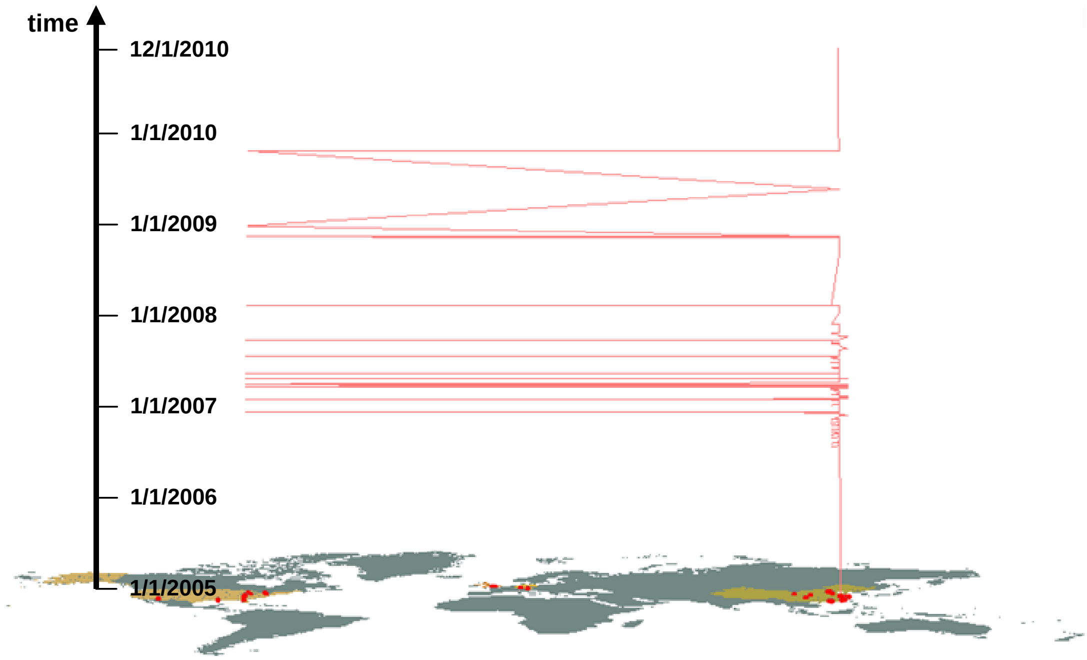
(c) Another angle to observe Guia’s virtual movements



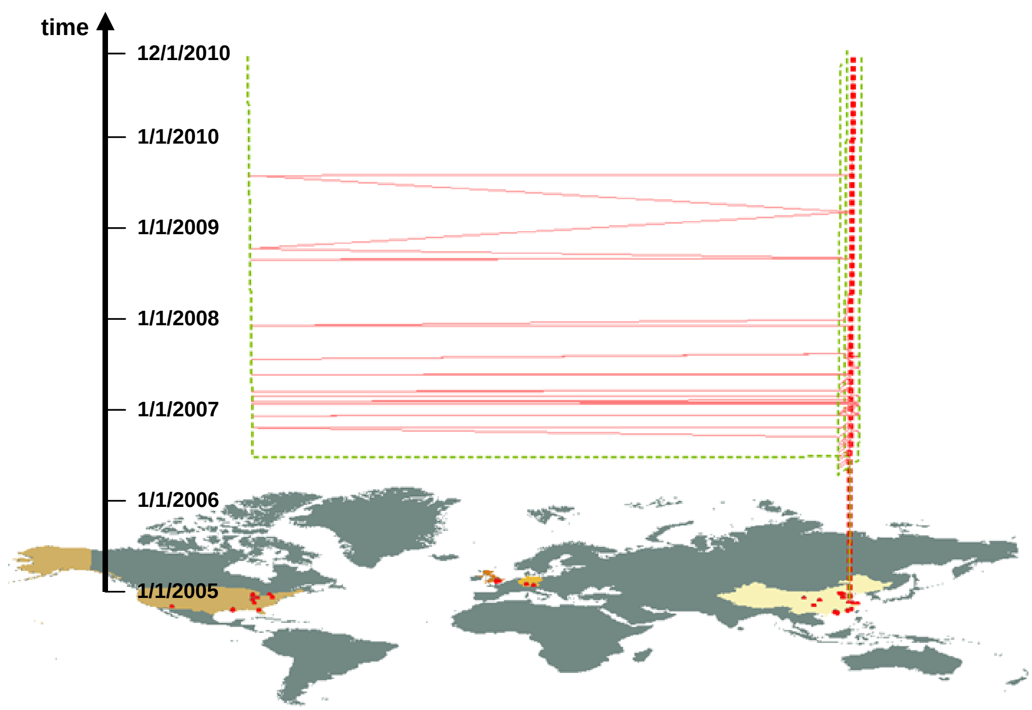

(d) Guia’s visits at her friend Nina’s place and the frequency of Nina’s new posts over the past six years

Figure 4.11 The virtual space-time path of a person who moved abroad

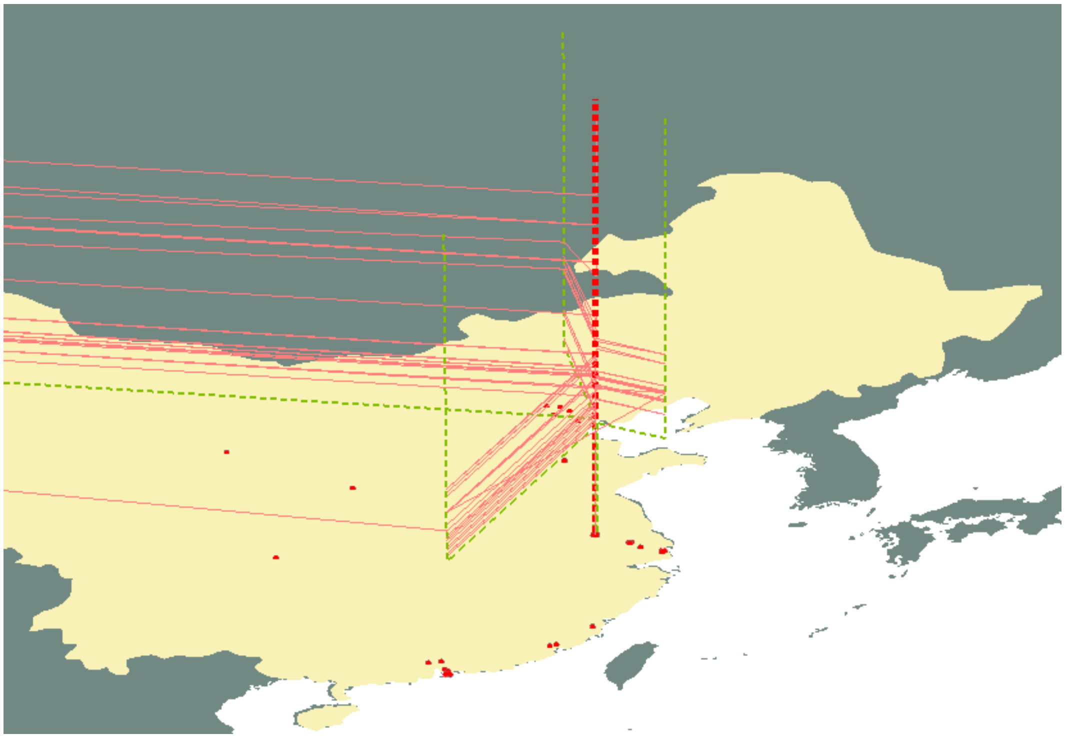
In another example of a virtual space-time path, Fay never moved out of Nanjing City after she graduated (Figure 4.12). During the past six years, she has had five close friends in the SNS space; four of them moved to other cities after graduation in 2006. In general, Fay's virtual space-time path shows different patterns in three phases. For most of the time before graduation in June 2006, Fay stayed at her own virtual place and occasionally visited her friends' virtual places (Figure 4.12d), which is more like the Type I pattern (Table 4.1). One possible reason for this pattern is that Fay did not need to talk with her classmates in the SNS space when they were still at the same university. In the following one and a half years after graduation, Fay became a typical Type III active user in the SNS space. Since Fay was away from her friends after graduation, she had to use the SNS space as a communication channel. Another possibility is that their friendship bonds were enhanced due to the loneliness of being in a new place or the excitements of starting a new career. However, after 2008 Fay became a Type V non-active user in the SNS space. Her virtual space-time path jumped across large temporal periods around her friends' places without staying at home. In other words, she almost stopped updating her own webpage and only occasionally visited her friends' webpages. Perhaps being apart for a year and a half resulted in some estrangement from her former classmates, or perhaps they switched to other communication means.



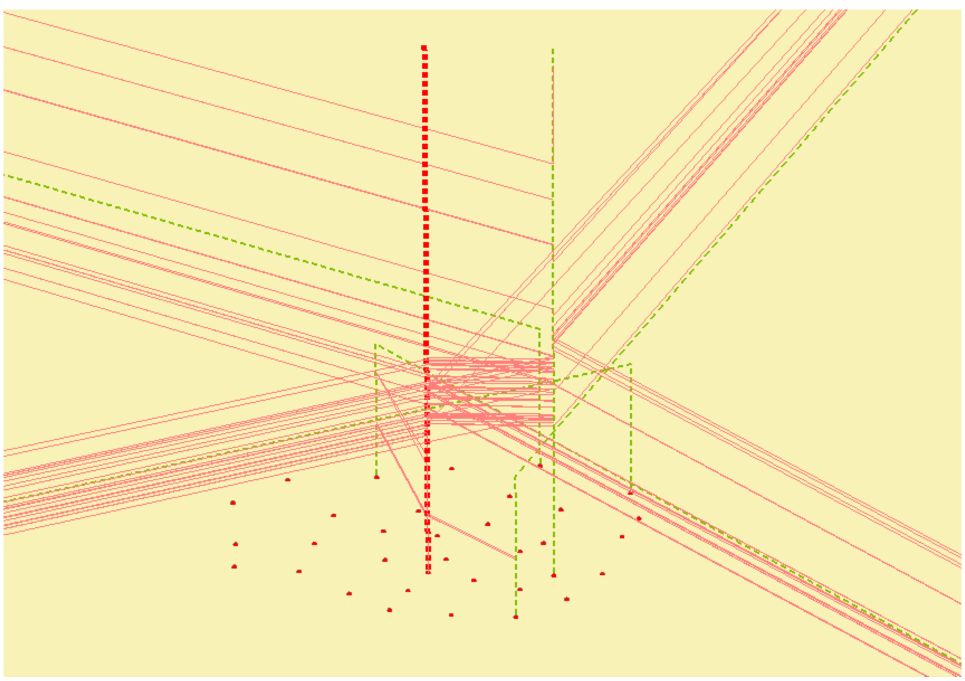

(a) Fay's virtual space-time path based on physical space-time paths




(b) Fay's virtual space-time path, her physical space-time path, and her visited friends' physical space-time paths



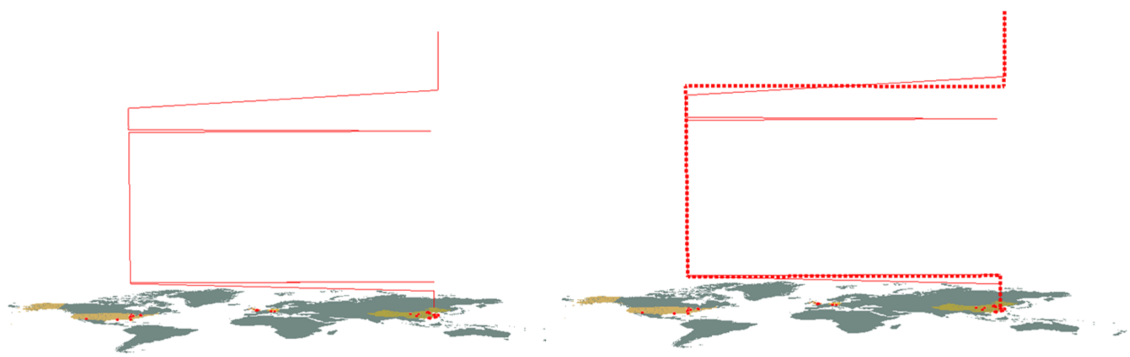
(c) At the scale of China



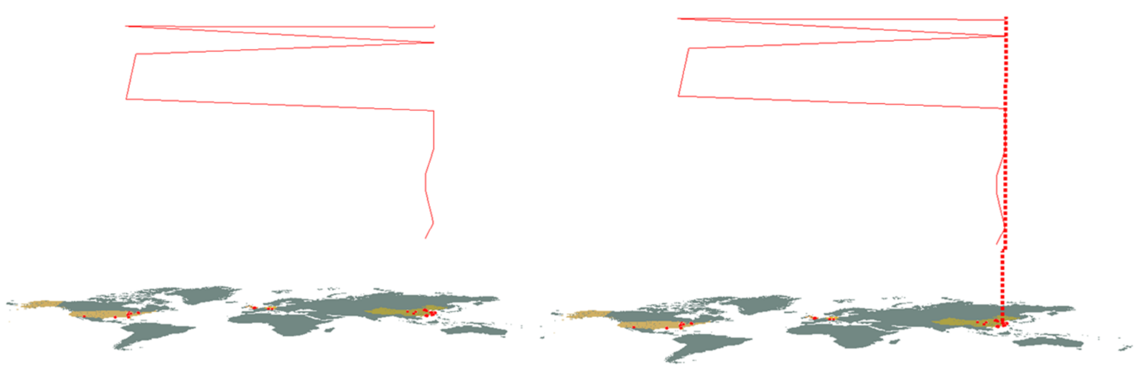
(d) At the scale of Nanjing City

Figure 4.12 The virtual space-time path of a person who never moved residency places

In the sample pool, on average 89% of participants were active users in SNS spaces during the past six years. Most of their virtual space-time paths exhibit obvious Type III patterns. Among the few active users with other types of patterns, one participant displays an obvious Type I pattern in his virtual space-time path (Figure 4.13a). Gordon's virtual space-time path almost exactly matches his physical space-time path. He regularly wrote new posts on his webpage, but almost never commented on his friends' webpages. Among the 11% non-active users' virtual space-time paths, the three types of non-active user's patterns all appeared in this study. For instance, Yane established a virtual space-time path with the Type V pattern (Figure 4.13b). She never posted on her own webpage and only occasionally commented on her friends' webpages: zooming to city level scale shows that her virtual space-time path never intersects with her physical space-time path, which cannot be easily observed at the worldwide scale.



(a) An example of a Type I virtual space-time path



(b) An example of a Type V virtual space-time path

Figure 4.13 Two examples of virtual space-time paths with rare patterns

So far this chapter has demonstrated the GIS function of creating virtual space-time paths based on physical space-time paths, as well as the patterns expressed by the participants' virtual space-time paths. The following three sections demonstrate a series of GIS functions that create and analyze social space-time paths, and that generate virtual space-time paths based on social space-time paths.

### *4.5.3 Social space-time paths*

The other approach this study proposes to represent virtual space-time paths is based on social space-time paths, which are generated by static Euclidean distance-based social networking graphs at different time stamps. A tool was developed to generate social space-time paths (Figure 4.14). There are three steps: create virtual distance matrix as inputs of MDS for each time interval, conduct MDS for each time interval, and rotate the output layouts of MDS to achieve the best layout stability.

The second step uses the MDS model embedded in the Matlab Automation Sever Type Library to conduct MDS. The MDS models in the Matlab library include classical MDS models and non-classical MDS models. Classical MDS models employ matrix algebra to obtain solutions, which will have identical results with principle component analysis (PCA) if using the Euclidean distances between points (http://www.mathworks.com/products/statistics/demos.html?file=/products/demos/shipping/stats/cmdscaledemo.html). Non-classical MDS models are optimization-oriented procedures, which are more flexible and more commonly used in recent decades. Non-classical MDS models also have two types: metric and non-metric MDS models (http://www.mathworks.com/products/statistics/demos.html?file=/products/demos/shipping/stats/

mdscaledemo.html). Metric MDS models create a layout of points so that their interpoint distances approximate the input distances, while non-metric MDS models attempt only to approximate the *ranks* of the input distances. This Tool invokes metric MDS models in Matlab library (http://www.mathworks.com/help/toolbox/stats/mdscale.html).

In addition to providing choices for input files and output files, this Tool offers six parameters that users can control (red dotted boxes in Figure 4.14);

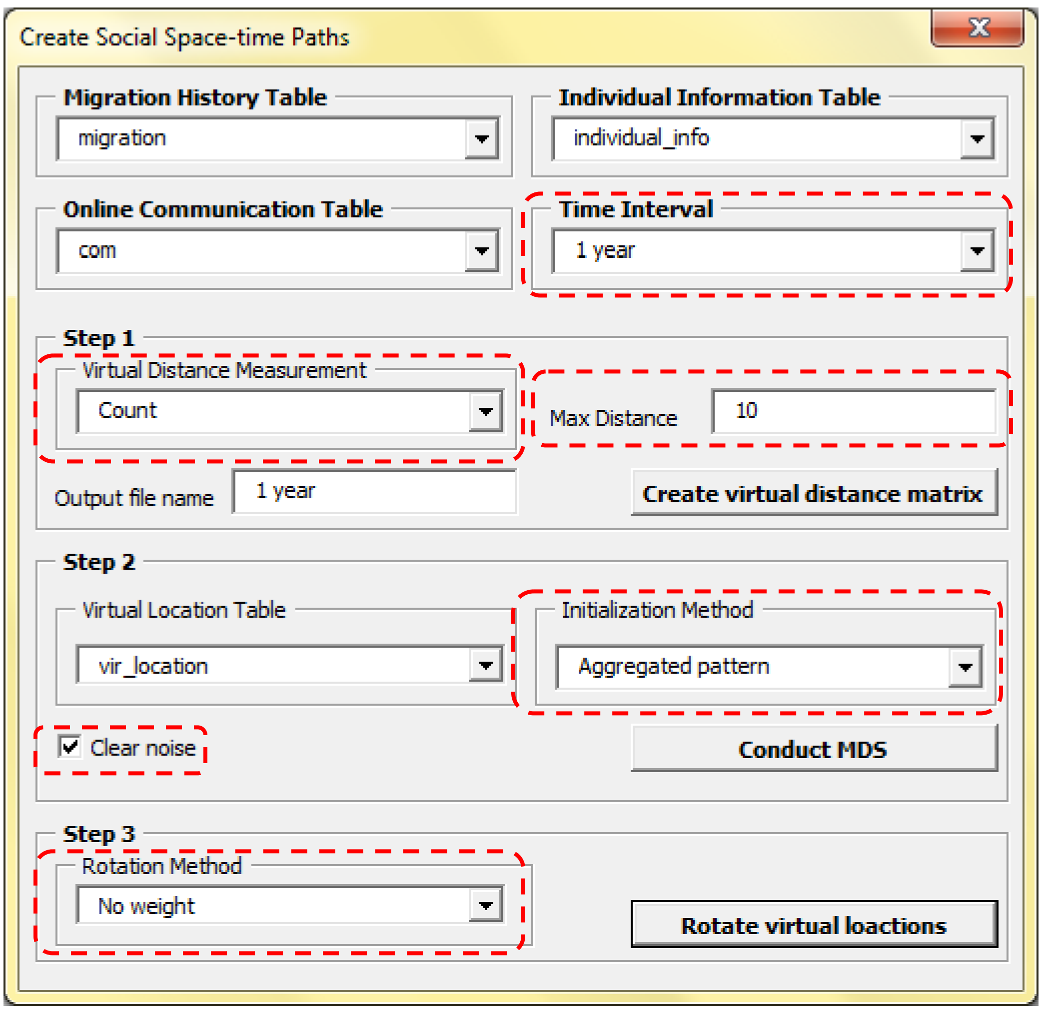



Figure 4.14 The function to create social space-time paths in ArcScene

1. Time interval: Time interval determines with which frequency a static social networking graph is generated. This study selected “6 years,” “1 year,” “6 months,” and “1 month” as options for time interval choices based on the sample data. For example, choosing “1 year” means a static social networking graph will be created for every year.
2. Virtual distance measurement: Two approaches are offered to measure “closeness” or “distance” between two people in an SNS space. Euclidean distance does not have direction, that is, the Euclidean distance from A to B is the same as that from B to A. Thus, to create a Euclidean distance-based graph, this study did not make distinctions based on the directions of the relationships between two people. For instance, person A might always leave messages on person B’s webpage, but person B never comments on person A’s webpage; the two directions of their relationship are not identical. This study treated “distance” between A and B as the total effect of the two directions of the relationship. Particular measurements include “Count” and “Visit probability.”

   Count distance is measured by the reciprocal of total visit times between two people. Due to the additive property of the measurement, the person who has the larger value of visit times contributes more to the measurement. For example, person A visits person B’s webpage 100 times, but person B visits person A’s webpage only once; their count distance is 1/101, dominated by person A. In other words, this measurement considers a one-way close relationship to be a close relationship. Virtual distance *VDis* based on communication count is:

$$VDis = \frac{1}{C(i \to j) + C(j \to i)} \tag{4-5}$$

where $C(i \rightarrow j)$ is the total times individual *i* visits individual *j* in an SNS space;

$C(j \rightarrow i)$ is the total times individual *j* visits individual *i* in an SNS space.

If the denominator is zero, a fixed maximum virtual distance must be used.

Probability distance is measured by the reciprocal of total visit probabilities between two people. Person A's visit probability to person B is the ratio of the times person A visits person B to the times person A visits all his/her friends; it represents the attention person A paid to person B relative to person A's attention to all friends. The total visit probabilities between two people reflect the total attention they paid to one another. As count distance, probability distance also is affected by the additive property of the measurement.

Virtual distance *VDis* based on visit probability is:

$$VDis = \frac{1}{\frac{C(i \rightarrow j)}{\sum_{j=1}^{n} C(i \rightarrow j)} + \frac{C(j \rightarrow i)}{\sum_{i=1}^{m} C(j \rightarrow i)}} \tag{4-6}$$

where $n$ is the total number of individual *i*'s friends in an SNS space;

$m$ is the total number of individual $j$'s friends in an SNS space.

If the denominator is zero, a fixed maximum virtual distance has to be used.

3. Max distance: This parameter sets the maximum virtual distance between two people who never communicated with one another. It affects the locations of non-active people in the MDS layout.
4. Initialization method: This parameter offers four types of initial seed for the metric MDS model: "Random," "Classical MDS," "Last pattern," and "Aggregate pattern." The "Random" method allows the MDS model to start searching with a random

layout. As discussed earlier, due to its instability this method is not recommended for creating a series of static layouts. The “Classical MDS” method first conducts the classical MDS model, and uses the result as the initial seed for metric MDS models. The initial layout of the “Last pattern” method comes from the MDS solution of previous time interval. For the first time interval, the solution of the classical MDS model will be used as initial seed by default. The “Aggregate pattern” method first conducts the metric MDS model with a classical MDS solution as initial seed based on the aggregate distance matrix of the entire study period. It then uses the solution as initial layout for the metric MDS model for each time interval.

5. Clear noise: Some individuals may not communicate with anyone else during a given time interval. Because these people’s many locations on the layout will mislead researchers, they are referred to as “noises” in MDS models. If the “Clear noise” checkbox is checked, the Tool will delete noises from the distance matrix and assign them locations specified only for noises.
6. Rotation method: Using the layout of the first time interval as a base, the rotation procedure rotates the layout of the second time interval to a degree that minimizes the instability between the two layouts. The procedure then uses the rotated second layout as the base and determines the rotation degree that minimizes the instability between the third layout and the second layout. The rotation procedure continues until it processes the layout of the last time interval. The instability of two layouts is quantified by *instability functions*. Each layout solution from the MDS model will be scaled into a coordinate system with $x$ ranging from -10 to 10 and $y$ ranging from -10 to 10. The rotation procedure will rotate a layout by each degree of 360 degrees to the

point (0, 0). The best rotation solution is the one that has the least value for the instability function. This study designed three instability functions corresponding to three rotation methods: "No weight," "Weight in center," and "Weight on anchors."

The "No weight" instability function sums up the distances between each individual's rotated location in the current time interval and his/her location in the previous time interval for all relevant individuals. Moving the same degree, individuals located in the peripheral areas will have more contribution to the value of the instability function than individuals in the central area. Moreover, if the "Clear noise" checkbox is checked, individuals who are noises in either of the two sequential time intervals will be excluded from the instability function.

The plain instability function $f(\alpha, t)$ without weights is:

$$f(\alpha,t)=\sum_{i=1}^{k}(\sqrt{(x_i^t(\alpha)-x_i^{t-1})^2+(y_i^t(\alpha)-y_i^{t-1})^2}) \tag{4-7}$$

where $f(\alpha, t)$ is the instability index between the layout in the *t-1th* time interval and the layout rotated by $\alpha$ degrees in the *t*th time interval; $(x_i^t(\alpha), y_i^t(\alpha))$ are individual *i*'s coordinates rotated by $\alpha$ degrees in the *t*th time interval; $(x_i^{t-1}, y_i^{t-1})$ are individual *i*'s coordinates in the *t-1*th time interval; *k* is the total number of relevant individuals. If the "Clear noise" checkbox is not checked, *k* is the number of all individuals. Otherwise, *k* is the number of individuals who are not noises in either of the two adjacent time intervals.

To balance the exaggerated effects for individuals located in the peripheral areas of a layout in the "No weight" instability function, "Weight in center" instability function adds weights to individuals based on their Euclidean distance to the center (0, 0).

The instability function weighted in center $f(\alpha, t)$ is:

$$f(\alpha,t)=\sum_{i=1}^{k}\left(\frac{1}{\sqrt{(x_i^{t-1})^2+(y_i^{t-1})^2}}\sqrt{(x_i^t(\alpha)-x_i^{t-1})^2+(y_i^t(\alpha)-y_i^{t-1})^2}\right) \tag{4-8}$$

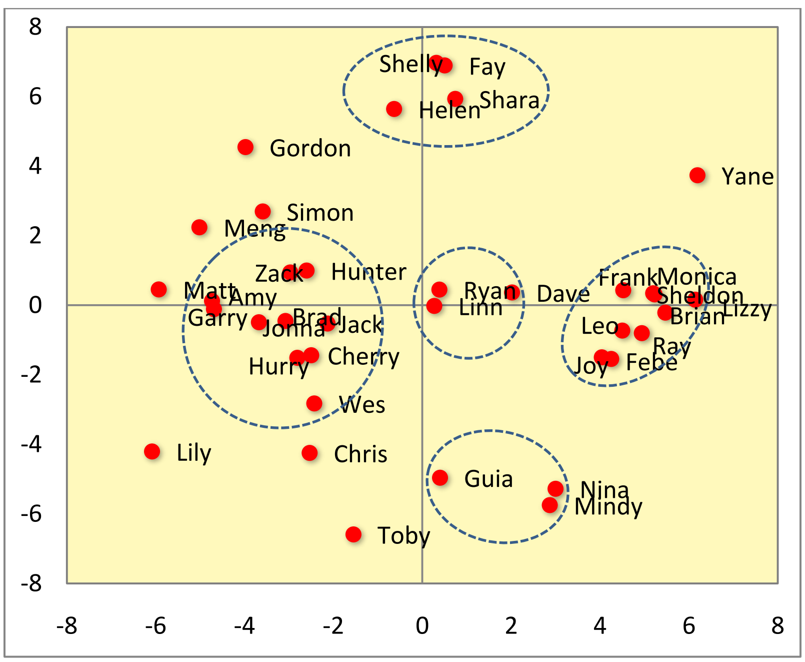
In some cases, researchers want to stabilize individuals they are interested in. "Weight on anchors" instability function only includes the individuals identified by researchers as anchors.

The instability function weight on anchors $f(\alpha, t)$ is:

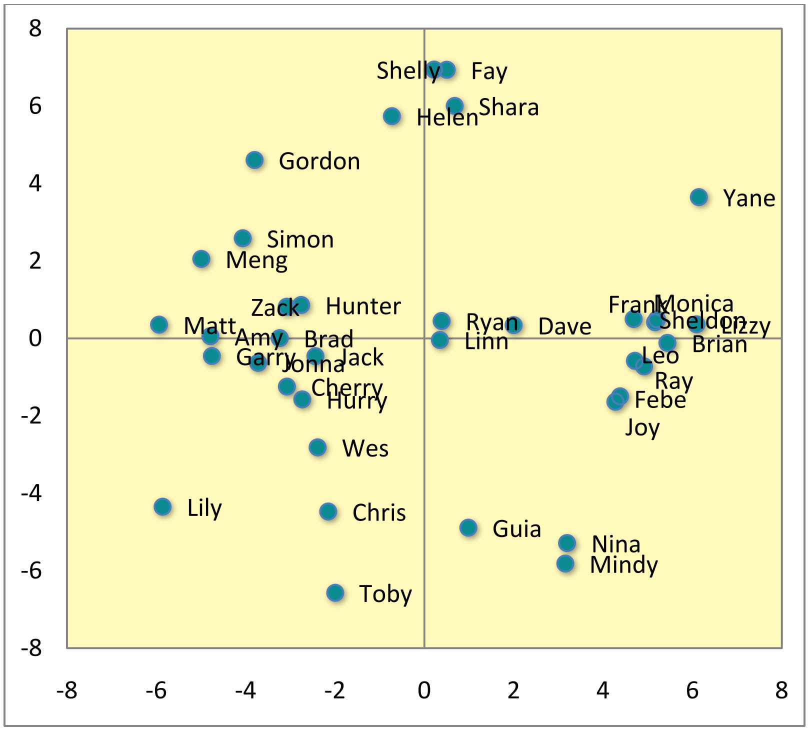
$$f(\alpha,t)=\sum_{i\_a=1}^{l}\left(\sqrt{(x_{i\_a}^t(\alpha)-x_{i\_a}^{t-1})^2+(y_{i\_a}^t(\alpha)-y_{i\_a}^{t-1})^2}\right) \tag{4-9}$$

where $i\_a$ is the individual indentified as an anchor; $l$ is the number of anchor individuals.

Virtual distance measurements define the fundamental relational layout among people. The choice of a virtual distance measurement depends on particular focus of any study. This study examined both count distance and probability distance. The Pearson correlation coefficient between count distance and probability distance for the entire study period was 0.68 (significant based on 0.01 level). The MDS solutions for the entire study period based on the two distance measurements were almost identical (Figure 4.15), which means that MDS solutions are not sensitive to the differences between the two measurements for the sample. This study thus used only count distance in the following experiments. Moreover, MDS layout does not guarantee that the Euclidean distance between any pair of people will match their original relationship in terms of a certain virtual distance measurement. For example, Ryan and Linn look like they are close in terms of communication count (Figure 4.15a). The original data shown that the communication count between Linn and Ryan was significantly less than between Linn and Frank (right to Dave). However, Linn and Ryan both played central roles in the social network, so their locations have to be in the center of the layout, which results in a misleading relationship between them on the map. Generally, people in the center—those who connect with more friends—have greater aggregate differences between their MDS mapped relationships with others and their original relationships with others by a certain measurement.




(a) The social networking graph of all participants based on count distance

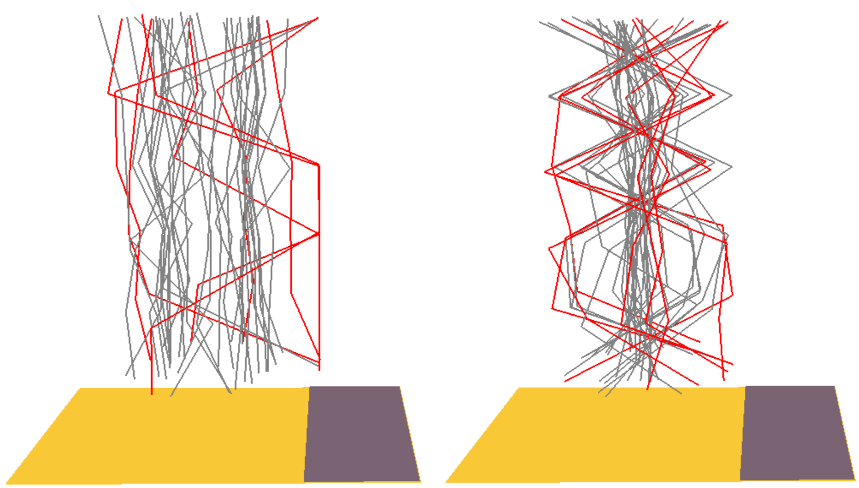



(b) The social networking graph of all participants based on probability distance

Figure 4.15 The layouts from MDS based on different virtual distance measurements.

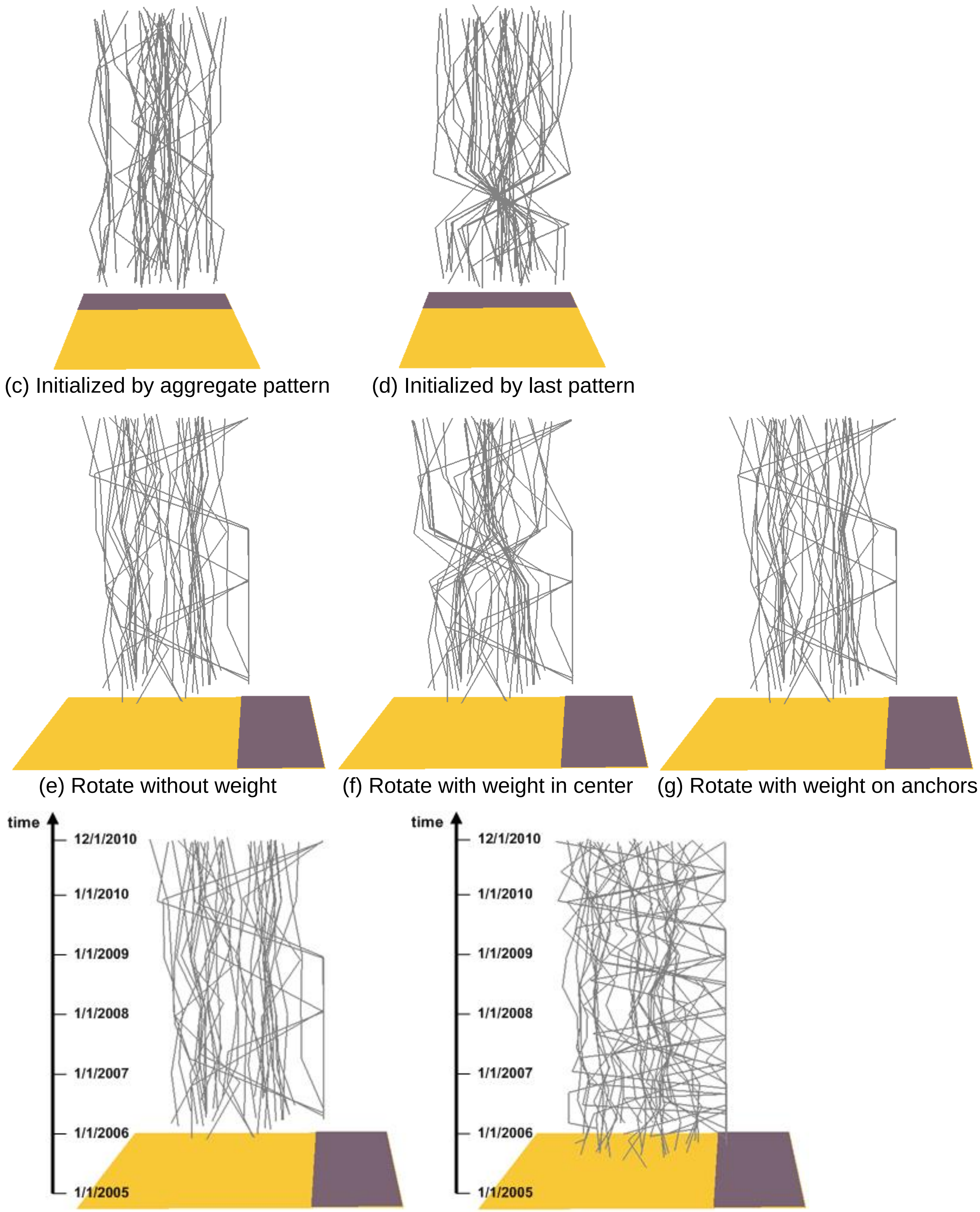
In the course of experimenting with various parameters, this study found that the max distance setting does not substantially affect active people's layout, but does influence non-active people's layouts. Setting an extremely great distance for a pair of people who do not communicate will force non-active people's locations to move toward to the center. A better solution is to set the max distance for people who do not communicate to a number several times greater than that calculated for people who do communicate with one another. For example, the maximum count distance calculated for people who communicate with each other is 1; setting the max distance for people who do not communicate to 10 will obtain a better layout than setting it to 10,000.

This study also compared the social space-time paths created by different parameter settings (Figure 4.16). With one-year interval and count distance, the parameter settings—clear noise, initialize by aggregate pattern, rotate without weight/with weight on anchors—generates a set of least intertwined social space-time paths (Figure 4.16h). With six-month interval and count distance, the parameter settings—clear noise, initialized by lasted pattern, rotate without weight/with weight on anchors—generate a set of least intertwined social space-time paths (Figure 4.16h). To conduct the rotation with weight on anchors, this study first manually identified several subgroups from the MDS layout for their relationships over the six years (each blue dashed circle includes a subgroup in Figure 4.15a). One individual was then selected from each subgroup in the social network as an anchor. Researchers can also use other ways to choose anchor individuals based on the research focus or assumptions.



(a) With noise control (b) Without noise control

(The yellow area represents a virtual space, and the purple area represents a particular space for noise. Red lines are noise.)




(c) Initialized by aggregate pattern

(d) Initialized by last pattern

(e) Rotate without weight

(f) Rotate with weight in center

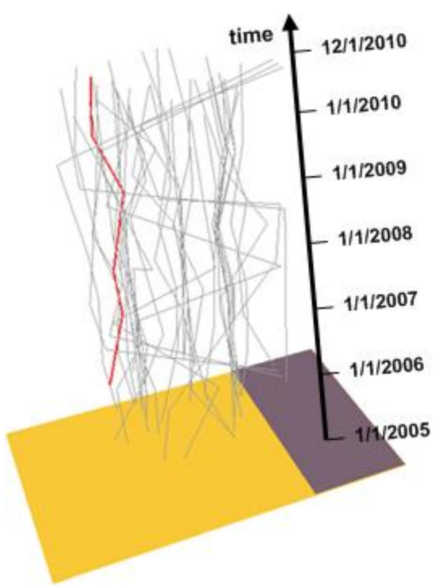
(g) Rotate with weight on anchors

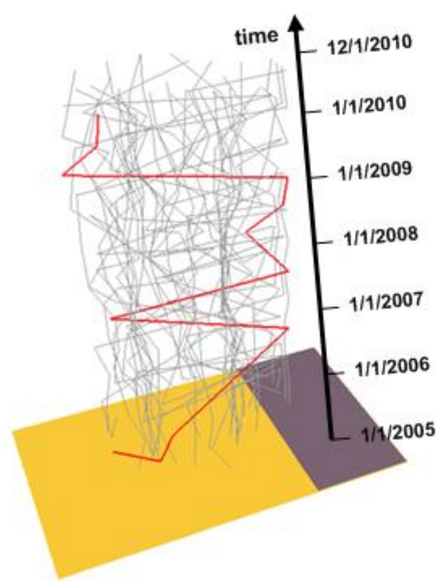
(h) One year interval

(i) Six months interval

Figure 4.16 Social space-time paths created by different parameter settings

Different time intervals reflect different temporal resolutions to investigate data. A wider time interval generally gives a set of smoother social space-time paths, while a set of social space-time paths with a narrower time interval reveals more details of the data. For example, Meng's social space-time path with one-year interval (red path in Figure 4.17a) shows his position as always located in a peripheral area within the entire social network and changing only in a limited extent over the six years. Such a pattern could be interpreted to mean that this person only communicated with a small group of people within the entire group, and his social networks did not change significantly over the last six years in the SNS space. Meng's social space-time path with six-month interval (red path in Figure 4.17b) uncovered more details. In fact, he did not leave any recordable activities in the SNS space in some periods of 2006, 2007, 2008, and 2009 and was mapped in the noise area (the purple area in the virtual space map). He jumped into the SNS space occasionally, and interacted with almost the same group of people, except sometime in 2008. To further explore with whom an individual interacted, his/her virtual space-time path must be examined.




(a) One-year interval (b) Six-month interval

Figure 4.17 An individual's social space-time paths in different time intervals

### 4.5.4 *Analysis on social space-time paths*

Unlike a virtual space-time path, a social space-time path does not represent an individual's every movement in virtual space, but approximately traces an individual's relative position within a social network over time. A collection of social space-time paths visualize a dynamic social network.

One important task of social network analysis is digging out subgroups or communities within the entire group and tracking the changes in subgroups over time. Current approaches for such a purpose focus on membership changes in a subgroup by identifying subgroups at each time interval, and then analyzing the changes in each subgroup at different time intervals. Most of these studies use animation to visualize dynamic social networks with a 2D map or trace an individual's membership with a subgroup-time graph (Leydesdorff *et al.*, 2008; Reda, 2009). Social space-time paths enable identification of subgroups with similar movement patterns within a social network over time, that is, allowing investigation of who moves together within a social network over time. Such capability adds a new perspective to investigations of dynamic social networks.

Cluster analysis was used in this study to identify subgroups with similar movement patterns. Instead of clustering people's locations at a static 2D map, this study conducted cluster analysis based on the similarities between social space-time paths. Several similarity measures for space-time paths have been proposed in recent studies (Laube *et al.*, 2005; Sinha and Mark, 2005; Shoval and Isaacson, 2007; Shoval *et al.*, 2010). This study measures the similarity *S* between two social space-time paths based on their average distance over time (equation 4-10; Figure 4.18). Figure 4.18 demonstrates an example of measuring similarity between two social space-time paths. The similarity between the two persons' social space-time paths is

$(d1 + d2 + d3 + d4)/4$. Other similarity measurements could be embedded in the cluster analysis tool in future research.

$$S = \frac{\sum_{t=1}^{n}\left(\sqrt{(x_i^t - x_j^t)^2 + (y_i^t - y_j^t)^2}\right)}{n} \tag{4-10}$$

where $(x_i^t, y_i^t)$ are individual $i$'s coordinates in the $t$th time interval; $(x_j^t, y_j^t)$ are individual $j$'s coordinates in the $t$th time interval; $n$ is the total number of time intervals.

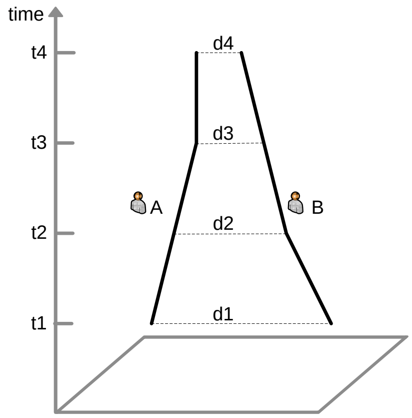



Figure 4.18 The similarity measurement for two individuals' social space-time paths

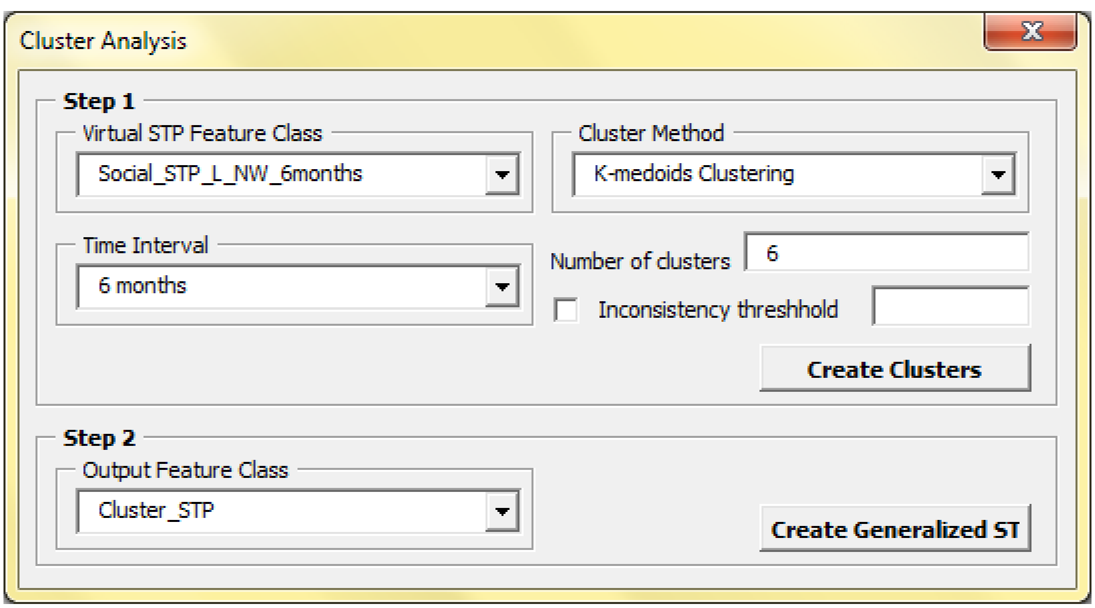
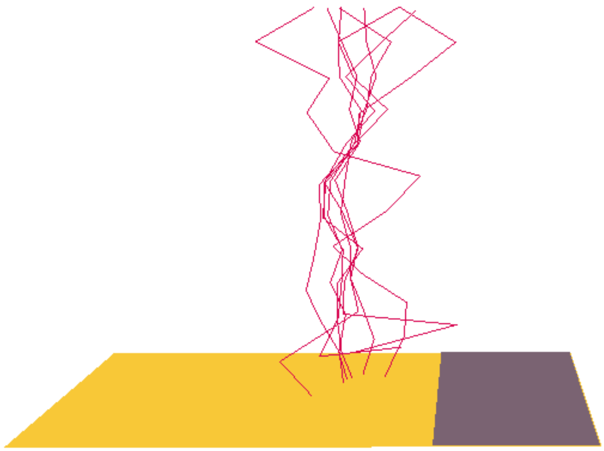



Figure 4.19 The tool to analyze social space-time paths

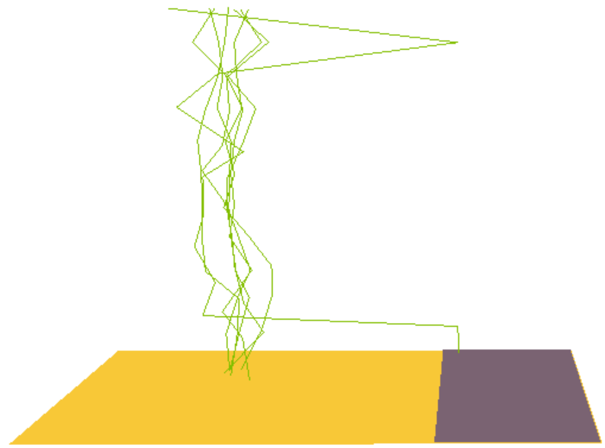
A tool was developed to conduct cluster analysis for space-time paths based on the similarity measurement (Figure 4.18; Step 1 on the interface in Figure 4.19). It works for all types of space-time paths, including physical space-time paths, virtual space-time paths, and social space-time paths. This tool offers the two basic types of cluster method: hierarchical and partitioning. It invokes the hierarchical clustering model in the Matlab library. Users can directly define, or use an inconsistency threshold to choose, the number of clusters http://www.mathworks.com/help/toolbox/stats/linkage.html. For partitioning methods, both *k*-means and *k*-medoids are commonly used. The key difference between the two is that *k* -means chooses group centers from any point on a map, while *k*-medoids choose group centers only from the original data points. Moreover, most *k*-means programs calculate distance between points using several common distance measurements such as Euclidean distance, Manhattan distance, and correlation coefficient. However, *k*-medoids can take any user-defined similarity matrix as the distance between points. Generally, due to the above differences, *k*-medoids are more robust regarding noise and outliers as compared to *k*-means (Kaufman and Rousseeuw, 1990). Therefore, the Tool chose *k*-medoids for the partitioning method option. The Matlab library for VBA environment does not include *k*-medoids models. This research developed a *k*-medoids model with Matlab script in the Tool, and invoked Matlab to conduct it backend.

As discussed in the last section, different time intervals reveal different aggregate levels of data. To demonstrate the Tool, this study chose six-month interval for the case study, which reaches a good compromise between simplicity for interpretation and richness in meaning (Figure 4.17i). The individuals who are identified as noise for most of the time intervals in the MDS operation are excluded from the cluster analysis. The cluster number is set to six, one more than the number of obvious subgroups in the social network layout over the six years (Figure

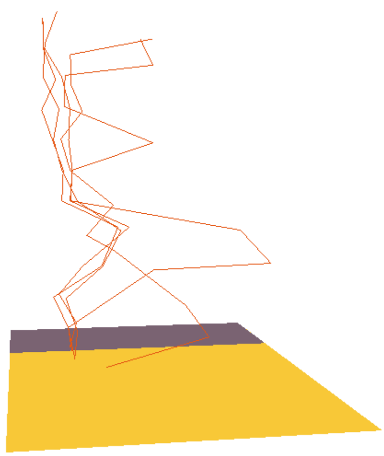
4.15a). Both hierarchical modal and *k*-medoids are tested, and the result of *k*-medoids model fits better for the dataset (Figure 4.20).



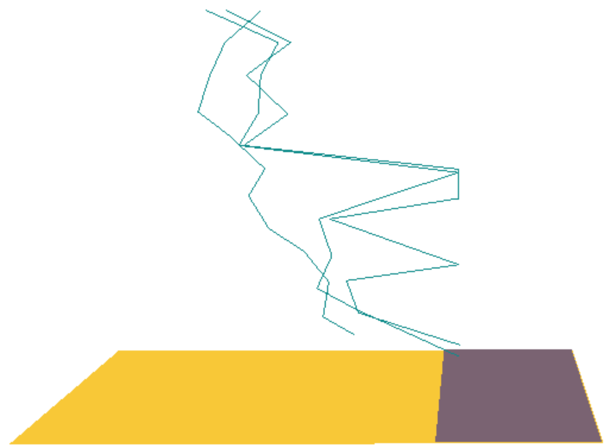
(a) Subgroup 1: degree=8



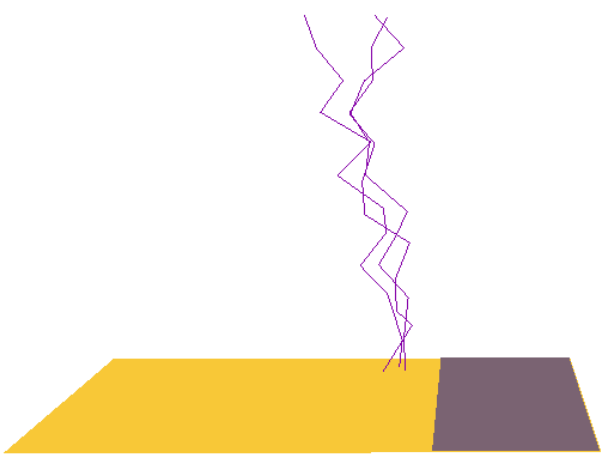
(b) Subgroup 2: degree=7



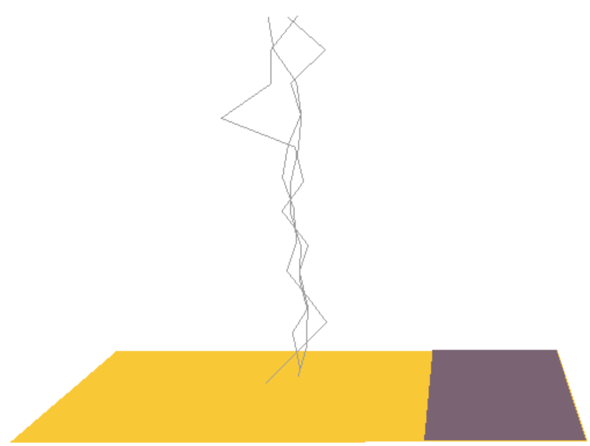
(c) Subgroup 3: degree=5



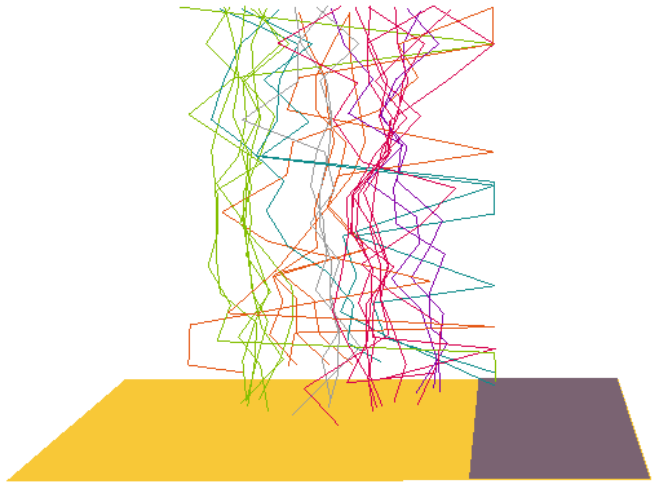
(d) Subgroup 4: degree=3



(e) Subgroup 5: degree=3



(f) Subgroup 6: degree=3



(g) All subgroups

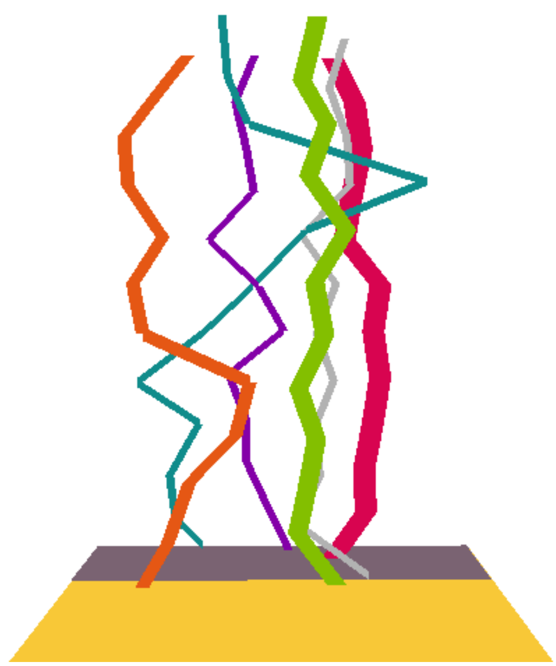
(Degree refers to the number of individuals in a group.)

Figure 4.20 Subgroups identified by *k*-medoids clustering method

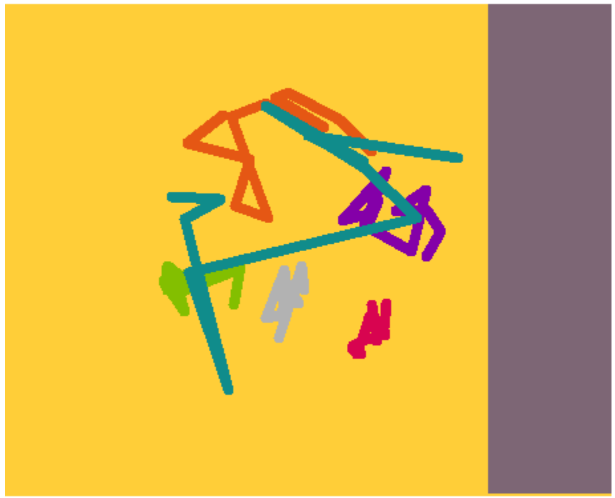
Cluttered paths make it difficult to interpret results when displaying all subgroups together to examine their relationships, (Figure 4.20g). Step 2 in the Tool therefore is to create a *generalized space-time path* for each subgroup, which reflects the aggregate pattern of space-time paths in a subgroup (Shaw *et al.*, 2008). The location of a generalized space-time path at a particular time interval is the average of the coordinates of all space-time path members in the subgroup at the time interval (Figure 4.21).

Group 1 (red), Group 2 (green), and Group 6 (grey) were relatively stable within the social network over the six years. Group 1 members all worked in the GIS laboratory during their master's studies, but graduated in different years. Group 2 members all entered the geography department as undergraduates in 1999, but never worked in the GIS laboratory. Group 6 members entered the geography department at the same year with Group 2 and also worked in the GIS laboratory during their master's studies, which explains why they are located in the middle of the two groups. All three stable groups are identified as mixed gender. Group 3 (orange) members were all the same gender, and all came from other universities to Nanjing University master's program except Mindy. Group 5 (purple) members all entered the geography department for undergraduate studies in 1998, studied abroad in the last six years, and were the same gender. Group 4 (blue) includes three students of the same gender who entered a same major for bachelor degree in the same year. Two Group 4 members had nearly identical social space-time paths during the six years, which indicates a close relationship between the two participants (Figure 4.20d). Moreover, Group 4 was the only group that moved across the social network over the six years. The members of Group 4 were close to those of Groups 3 and 5, but became closer with Group 2 in the more recent three years. To sum up, subgroups in the sample in the SNS space were affected by academic major, year of entering the department, and gender.

(a) Side view



(b) Side view (horizontally rotated 90 degrees)

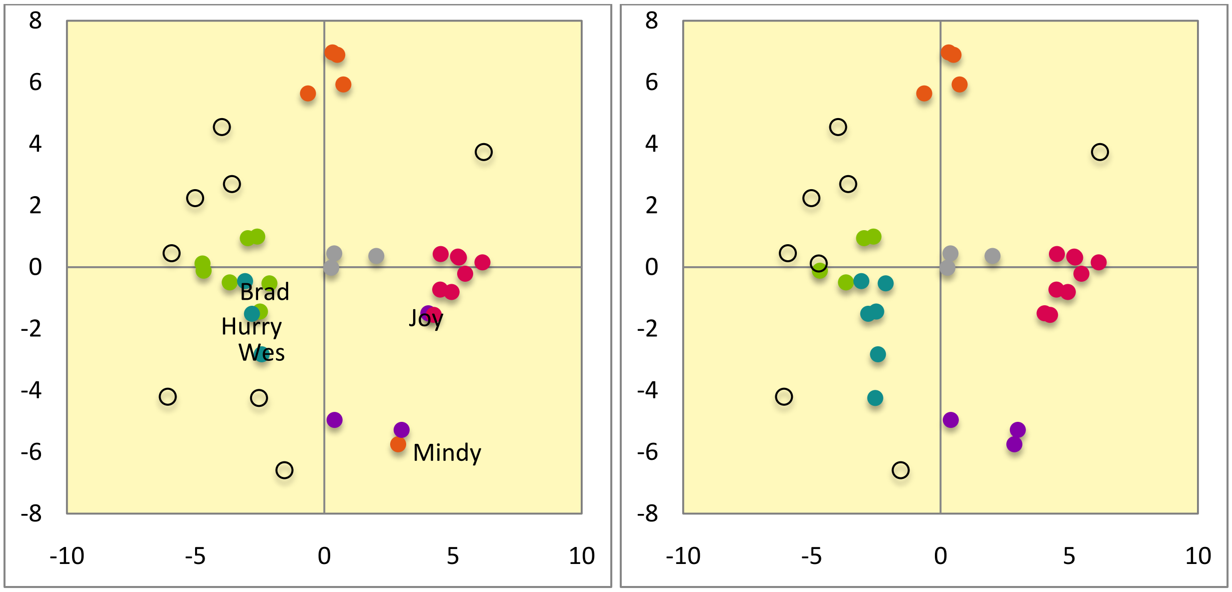


(c) Bird's eye view

Figure 4.21 Generalized social space-time paths based six-month interval

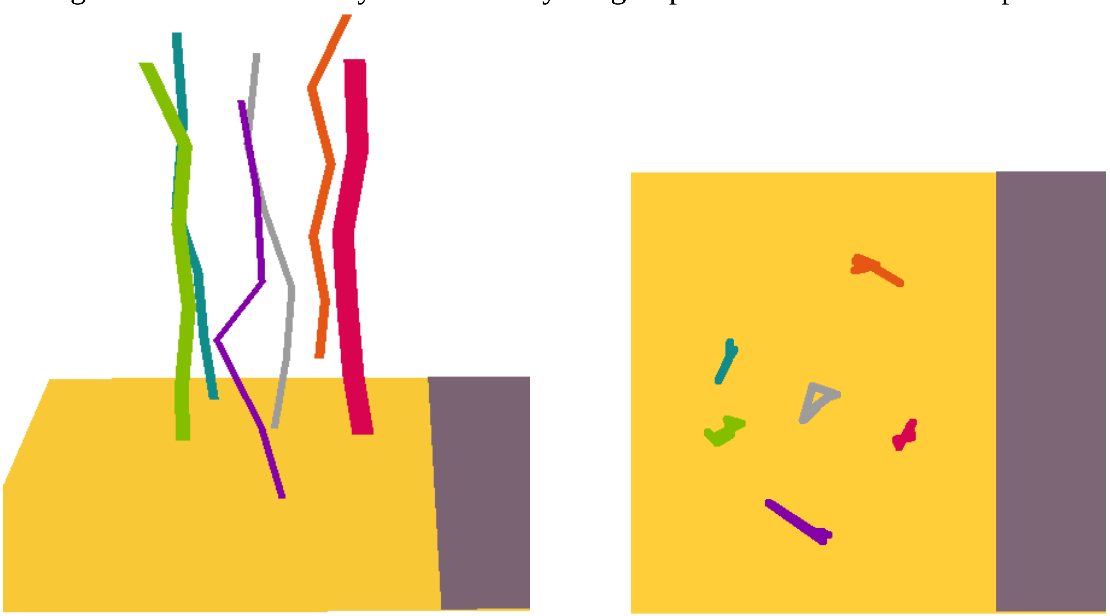
The cluster approach proposed in this study considers the entire history of an individual's position within a social network in similarity between people. Figure 4.22a uses Figure 4.15a as the layout base, and colors individuals by their subgroups as shown in Figure 4.21. Due to the fact that the MDS layout based on the degree of aggregate communication in the six years also considers the total effects of the subjects' relationships during the entire period, it has patterns similar to those in Figure 4.21. However, an aggregate pattern does not reflect individual movements in a social network changes over time, which is not able to reveal the unique pattern of Group 4 (Brad, Hurry, and Wes). Joy and Mindy also had significant changes in their social networks over time, so the degree of their aggregate communication and their movement patterns within the social network exhibit different identities.

As the time interval of creating social space-time paths widens, more movement details will disappear, and the subgroup pattern based on social space-time paths will become more consistent with the MDS layout based on the degree of aggregate communication over the course of the entire study period. Figure 4.23 shows the generalized social space-time paths based on subgroups identified by social space-time paths with one-year intervals. Figure 4.22b identifies individuals by their subgroups based on one-year intervals, which is almost identical to the subgroup pattern on the MDS layout. Thus, the approach presented in this study to analyze dynamic social networks is sensitive to the choice of temporal resolution.




(a) Subgroups based on six-month interval (b) Subgroups based on one-year interval

Figure 4.22 The MDS layout colored by subgroups identified from social space-time paths



(a) Side view (b) Bird's eye view

Figure 4.23 Generalized social space-time paths based one-year interval

So far this chapter has discussed the approaches creating social space-time paths as well as analysis based on social space-time paths. In the next section, the other representation of virtual space-time paths based on social space-time paths will be discussed.

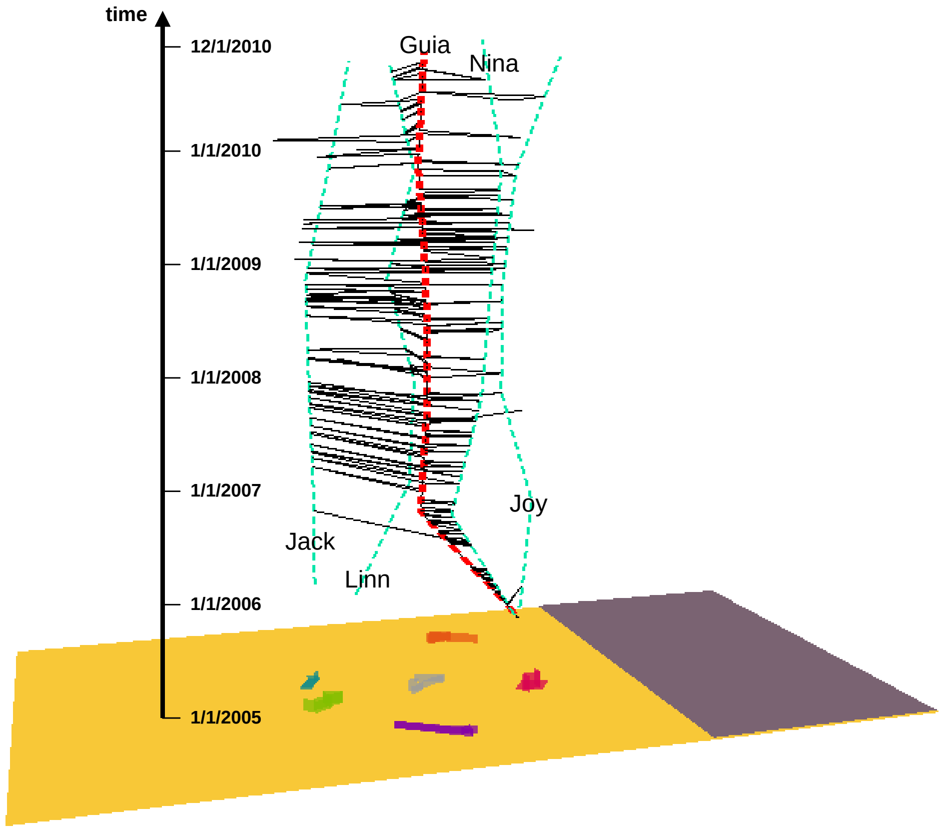
### *4.5.5 Virtual space-time paths based on social space-time paths*

More stability in people's virtual places will generate less intertwined virtual space-time paths. To demonstrate virtual space-time paths based on social networking graph, this study chose social space-time paths with one-year intervals as the subjects' migration patterns in virtual space (Figure 4.16h). Setting "residency place history feature class" to the social space-time path feature class, the virtual space-time path generator created all participants' virtual space-time paths based on their social space-time paths (Figure 4.10).

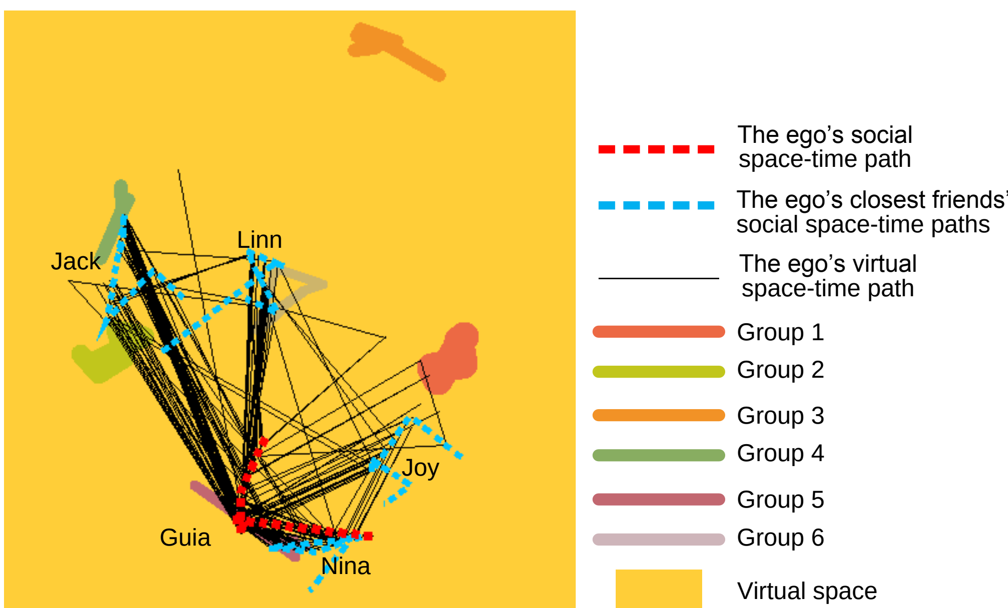
To compare the two ways of representing virtual space-time paths, this section refers to the four individuals mentioned in Section 4.5.2 as examples—Guia, Fay, Gordon, and Yane. Figure 4.24 shows Guia's virtual space-time path, her social space-time path, and the social space-time paths of the four friends with whom she communicated most. Nina, in the same subgroup with Guia, is the only friend with whom Guia communicated in SNS space before 2007. Then Guia gradually began to interact with Jack (Group 4), Linn (Group 6), and Joy (Group 1). In the meantime, Nina became less active in SNS space, and the communication between Guia and Nina dropped sharply in later years (Section 4.5.2). Accordingly, their social space-time paths show that the distance between Guia's location and Nina's location in the social network increases with time (Figure 4.24a).

Figure 4.25 displays the virtual space-time paths and social space-time paths of three other participants, revealing the same movement patterns as shown in their virtual space-time paths based on physical space-time paths (Figure 4.12 and Figure 4.13). Moreover, it is easier to observe movement patterns based on a social networking graph, which has a better unified map scale than geographical maps with hierarchical spatial scales (e.g., world level, country level, city level). For instance, Yane visited the web pages of her friends who lived in the same city with her. In Figure 4.13b, unless zooming in to the city level, it is difficult to determine whether she visited her own place or her local friends' places, which leads to confusion between Type V and Type VI patterns of use. In Figure 4.25c, however, it is obvious that she is a typical Type V user.

The two approaches to representing the virtual movements of individuals in an SNS space complement each other and can be summarized as to their advantages and limitations (Table 4.3). These findings can be explained as follows:




(a) A 3D view




(b) A 2D view

(Ego refers to the individual of interest.)

Figure 4.24 An individual's virtual space-time path based on social networking graph

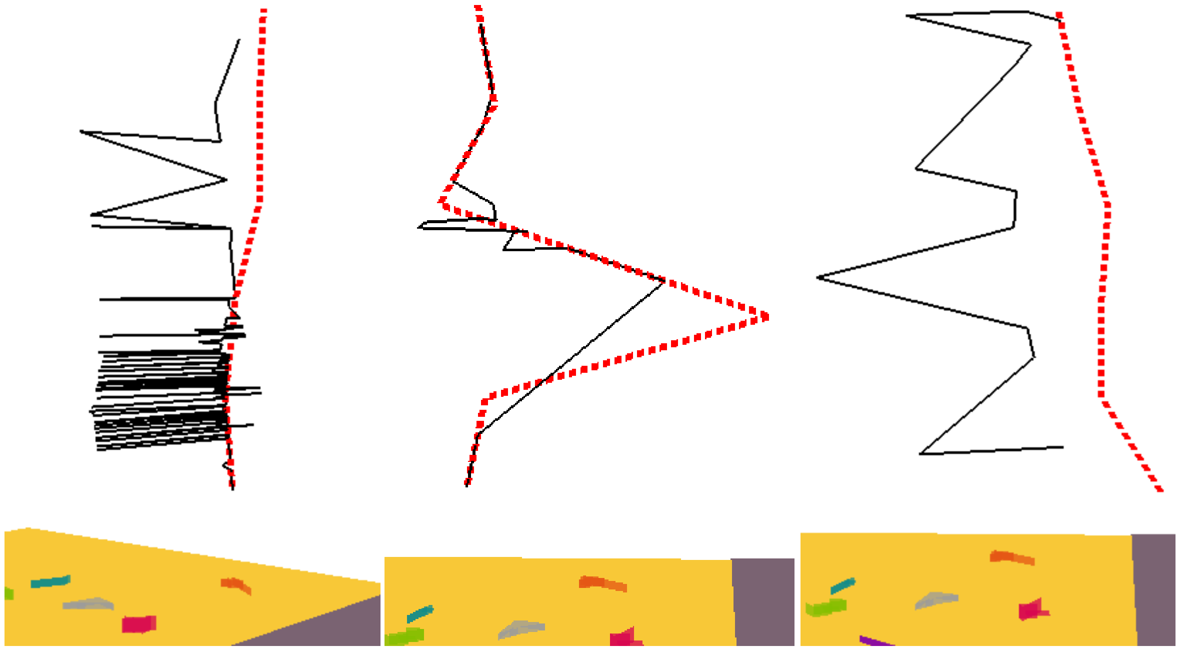



Figure 4.25 Examples of virtual space-time paths with different movement patterns

Table 4.3 Comparison of two representations of virtual space-time paths

| | Based on physical space-time paths | Based on social space-time paths |
|---|---|---|
| Visualizes virtual movement patterns | Yes | Yes |
| Represents individuals' geographical locations | Yes | No |
| Represents geographical distance | Yes | No |
| Represents individuals' social groups | No | Yes |
| Represents "closeness" by map distance | No | Yes |
| Analyzes dynamic social networks | No | Yes |
| Handles a large population | Yes | Limited[a] |
| Spatial scale free | Limited[b] | Yes |
| Temporal scale free | Yes | Limited[c] |

(a: The performance of MDS models generally decreases with the increase of subjects. An MDS layout of a large population may have significant differences from the original similarities/dissimilarities (Section 4.5.3 discussed an example of Linn and Ryan in Figure 4.15a). A compromised way to represent social aspects in virtual space-time paths for a large population is to use topological distance-based social network graph. b: The interactions of people in a large spatial scale such as in a city cannot be easily shown in a small spatial scale such as a worldwide view. This problem can be solved by adjusting zooming levels and vertical exaggeration levels in ArcScene. c: The choice of time interval will influence shapes of virtual space-time paths.)

### 4.5.6 Virtual space-time prisms

This study was able to explore their probabilistic virtual space-time prisms for the SNS of a selected group of people. A tool was developed to generate an individual's probable virtual space-time prisms and the probabilities of two individuals' synchronous interaction on a particular day of the week based on their communication history in an SNS space (Figure 4.26). The predicted temporal range is one day (24 hours), and the temporal resolution is one hour. The first step was to create the subjects' virtual locations for the specified day. To avoid geographical scale problem and to better represent people's social distance, this Tool used MDS to create the subjects' virtual layout. Users have to set the temporal range of communication records as the prediction reference. In this study, the last three months in the study period were selected as the reference period. In step 2, users need to select two persons of interest. Because people might have different activity patterns in an SNS space on different day of week, especially between weekdays and weekends, the Tool also offers options to choose the day of week for prediction. The predicted day is the selected day of week after the end of the communication history range based upon person A's time zone. For example, if Monday is chosen, the predicted day based on the period between 9/1/2010 and 11/30/2010 will be a Monday after 11/30/2010.

Several active SNS users and their interaction scenarios are selected to demonstrate access and social network constraints on virtual activities and interactions in an SNS space (Table 4.4 and Table 4.5). In all four scenarios, this study designated Jack as person A who sets the time zone for the analyzed day.

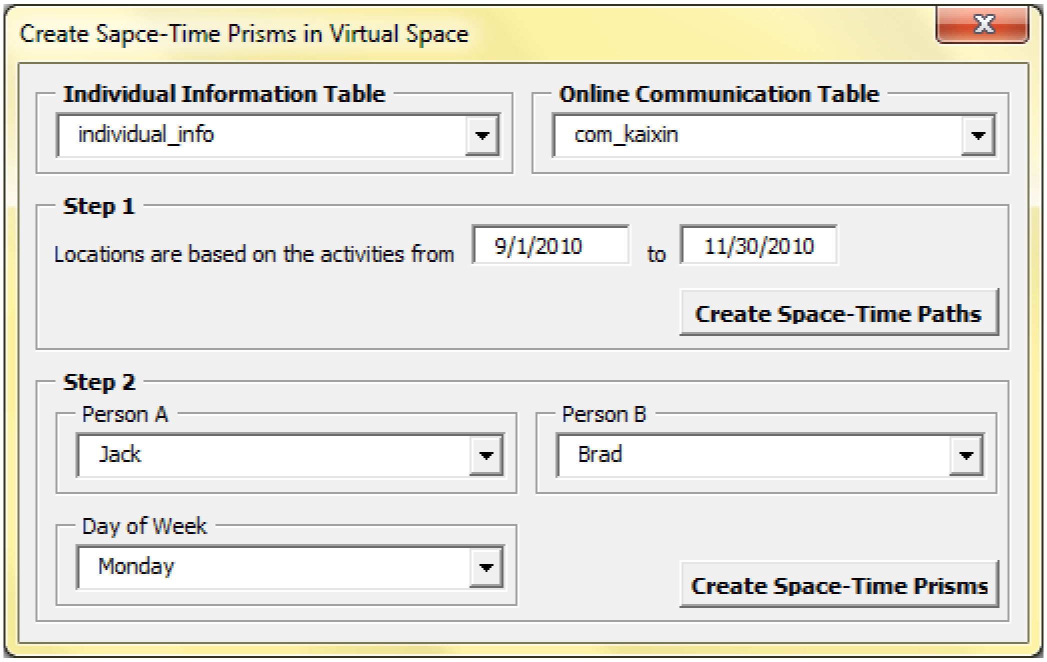



Figure 4.26 The Tool to generate probabilistic virtual space-time prisms

Table 4.4 Selected individuals for space-time prism analysis

| Participant | Occupation | Local time zone | SNS user type |
|---|---|---|---|
| Jack | Graduate student | US Eastern Time | Daily active user[a] |
| Brad | Working | US Eastern Time | Daily active user |
| Zack | Working | China Beijing Time | Daily active user |
| Ray | Working | China Beijing Time | Daily active user |

(a: a daily active user refers to an individual who in average has at least one recordable activity in an SNS space per day.)

Table 4.5 Selected scenarios for virtual interaction analysis

| Scenario | In the same time zone | SNS Friends | Day of week (US Eastern Time) |
|---|---|---|---|
| Scenario 1: Jack-Brad | Yes | Yes | Monday |
| Scenario 2: Jack-Zack | No | Yes | Monday |
| Scenario 3: Jack-Ray | No | No | Monday |
| Scenario 4: Jack-Ray | No | No | Saturday |

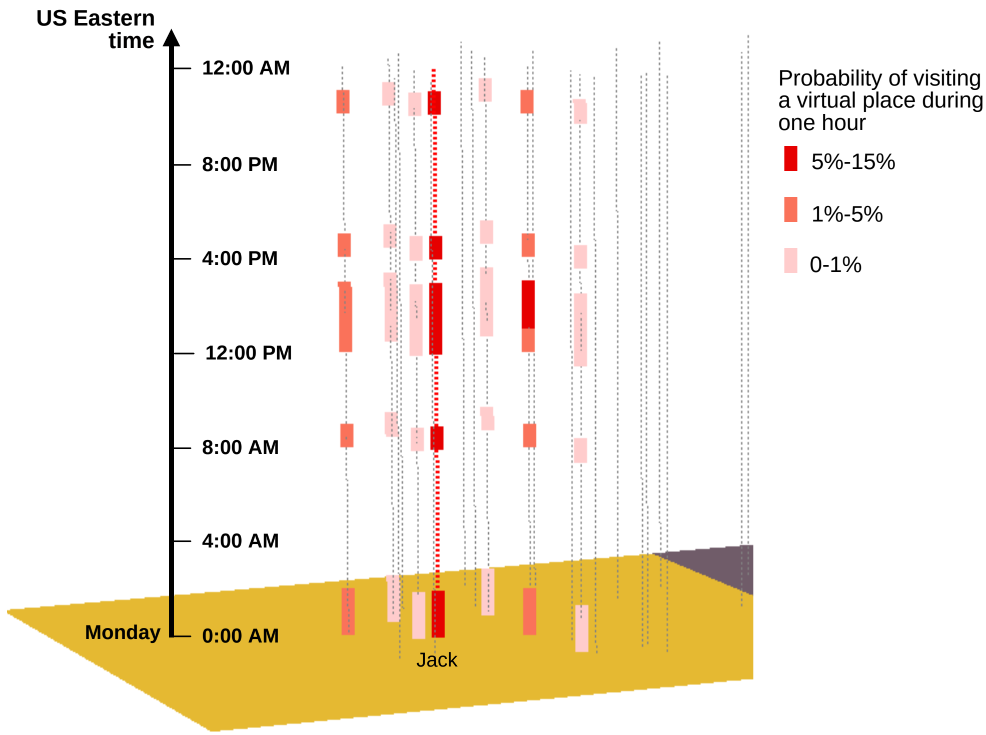
In scenario 1, Jack and Brad both lived in the eastern US. Jack is a graduate student, so his online time was flexible even it was on a weekday (Figure 4.27 a). His online time periods on the Mondays of the last three months covered in the study were scattered in periods of the middle of the night (0:00 AM – 2:00 AM), early morning (8:00 AM – 9:00 AM), mid-afternoon (12:00 PM – 3:00 PM, 4:00 PM – 5:00 PM), and late night (10:00 PM – 11:00 PM), which display the typical day of a graduate student. He remained in the SNS from Sunday night until Monday morning, went to sleep, got up early on Monday morning, probably to attend class, checked new updates in his SNS before class, stayed away from SNS during classes or while studying in the morning, logged into an SNS again in the afternoon and probably remained there for whole afternoon if his schedule permitted, then went to dinner, participated in some social activities, studied at night, and as a last act checked the status of friends in a SNS before going to sleep. On the other hand, Brad was working, which might explain why he spent less time online on Monday compared with Jack (Figure 4.27b). These patterns indicate that access constraints limit online time probabilities. Moreover, Jack had more friends in the SNS space than Brad, which is revealed by their relative locations in the virtual map: Jack locates more toward to the center than Brad does in Figure 4.27a and b). Due to social network constraints, Jack could visit more virtual places than Brad.

People will automatically log into their own web pages in an SNS space, so the probability of visiting their own virtual places during the online time is set to 100% by default and the equation is $P(A \rightarrow A)_{T_k} = 1 \times P(A|T_k)_{\tau}$ (see equation 4-1). Due to that setting, the probabilities of Jack and Brad being in their own virtual places are higher than being in their friends' virtual places. Of course, this setting can be changed to other measurements, such as calculating the probability that people conduct recordable activities on their own web pages, which might be more reasonable for Type II or Type V users.

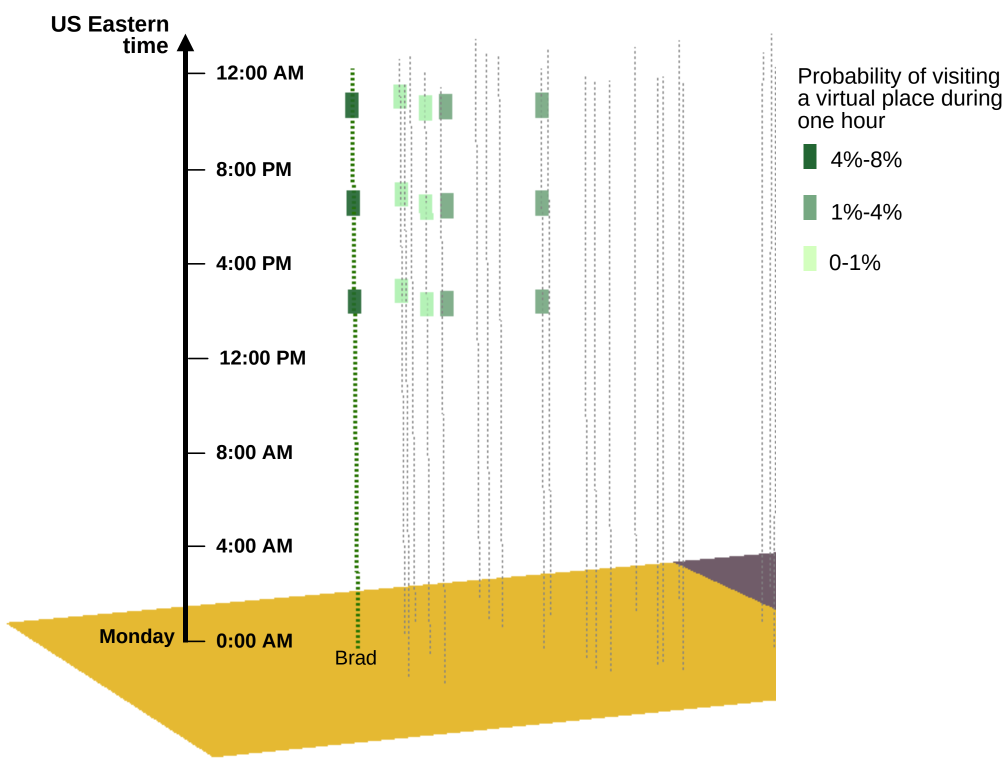
Figure 4.28a shows synchronous interaction probabilities between Jack and Brad in the SNS space on Monday. There are two time windows during which they could have left messages at the same virtual places, which include their own web pages and the web pages in the SNS space of three common friends. During the two time windows, they might have commented on the same post of a common friend and communicated with each other instantly in the SNS space. In scenario 2, Zack was working in China, where the time zone is 12 or 13 hours ahead of US Eastern Time (depend on summer time or winter time in US). Based on the setting in Figure 4.26, the predicted day is in winter, so 0:00 AM – 12:00 AM on Jack's Monday is from 1:00 PM Monday to 1:00 PM Tuesday for Zack. Figure 4.27c shows Zack's space-time prisms during the 24 hours. He was active on Monday night and occasionally entered the SNS space on Tuesday morning. The synchronous interaction opportunities between Jack and Zack appear at only two time windows (Figure 4.28b). One was in Jack's early morning, which was Zack's night; the other one was in Jack's late night, which was Zack's noon. Although Jack and Zack were both daily active users and both played central roles in this social network, their instant communication opportunities were limited by their significant spatial-temporal distance on the earth.

In scenario 3, Ray was also working in China, but he was not a friend of Jack in the SNS space. He had online time windows from Monday afternoon to Tuesday morning similar to those of Zack, but visited fewer friends than Zack (Figure 4.27d). The only time window for Jack and Zack to have synchronous interactions was on Jack's Monday morning on the web pages of two mutual friends. Both access constraints and social network constraints shaped the intersection of their virtual space-time prisms.

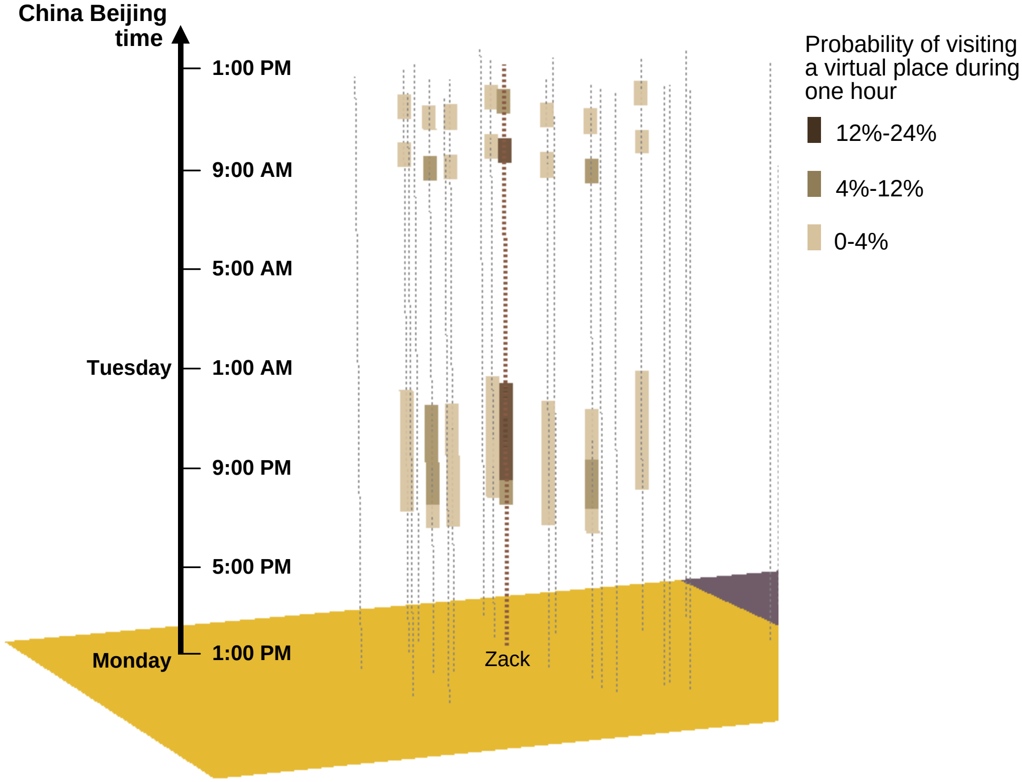
In scenario 4 for Jack and Ray, the predicted day changed from Jack's Monday to Jack's Saturday. On Saturday, Jack only showed up in the SNS space after 12:00 PM, probably because he arose later on weekends (Figure 4.27e). On the other hand, Ray was active on Sunday mornings, probably because he did not need to work, and weekends were his time for contacting old friends (Figure 4.27f). As a result, they had synchronous interaction opportunities on Jack's Saturday night (Ray's Sunday morning), still on their two mutual friends' virtual places (Figure 4.28d).



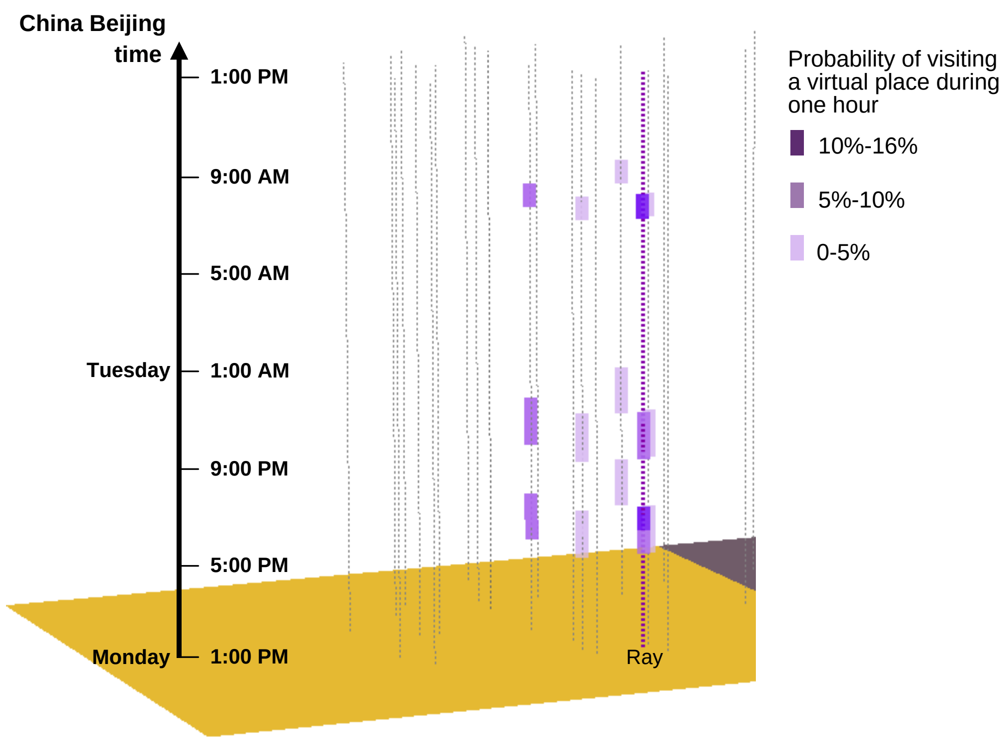
(a) Jack's space-time prisms on Monday in US Eastern Time



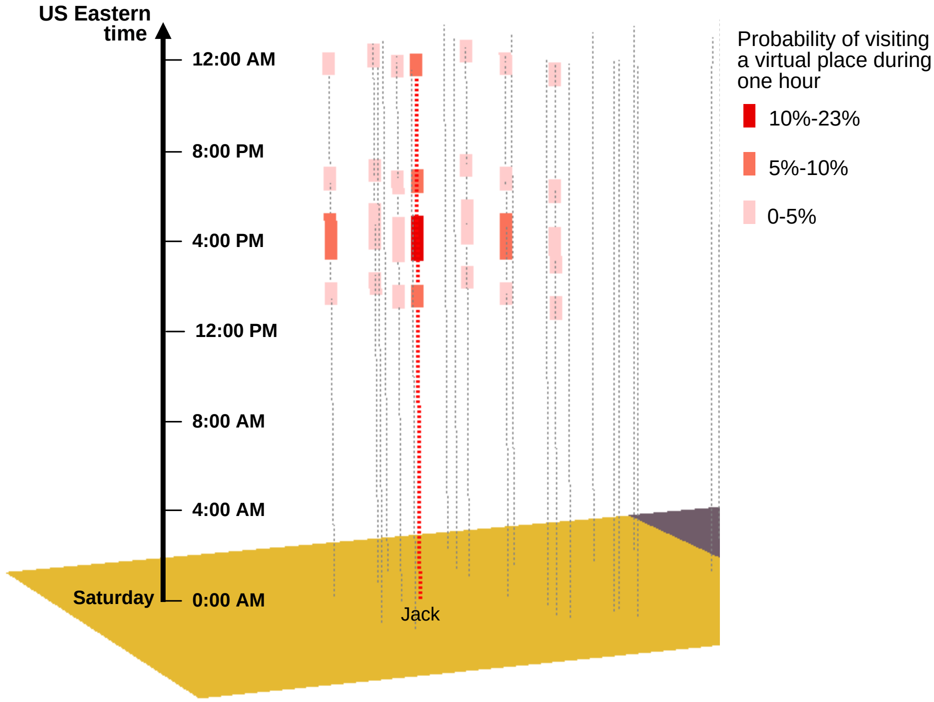
(b) Brad's space-time prisms on Monday in US Eastern Time



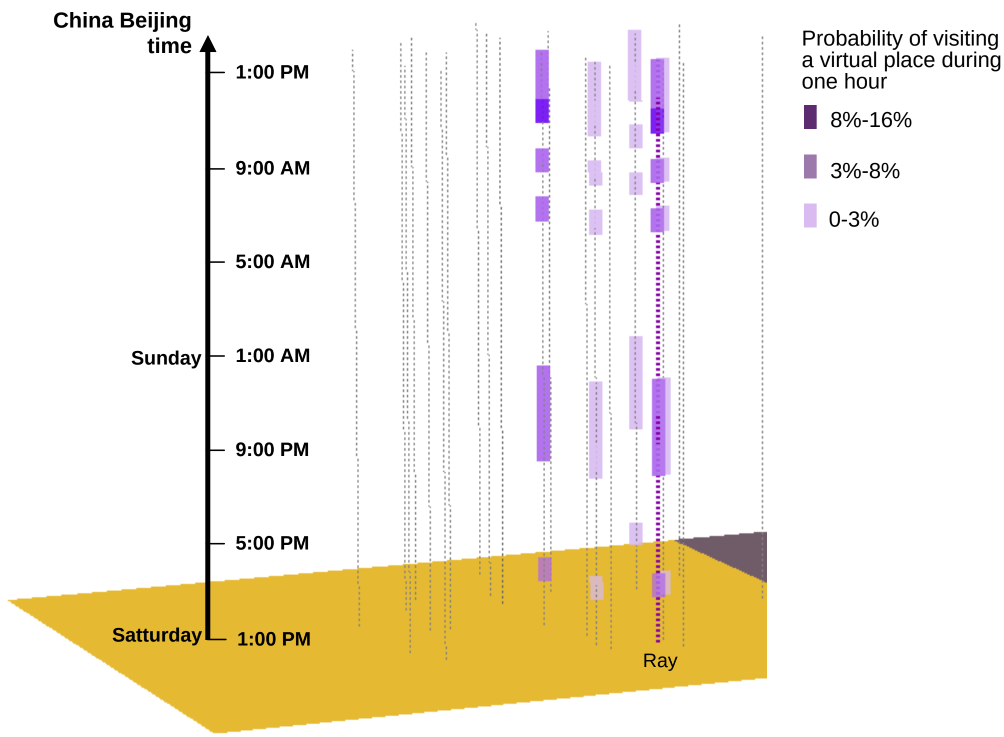

(c) Zack's space-time prisms on Monday in US Eastern Time




(d) Ray's space-time prisms on Monday in US Eastern Time

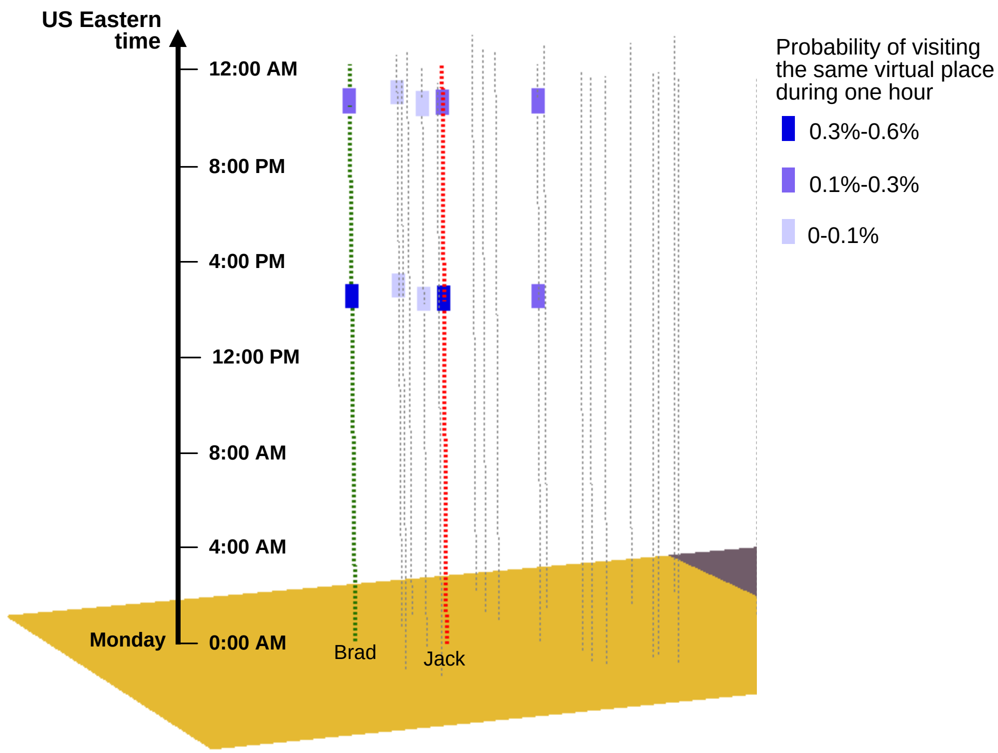



(e) Jack's space-time prisms on Saturday in US Eastern Time

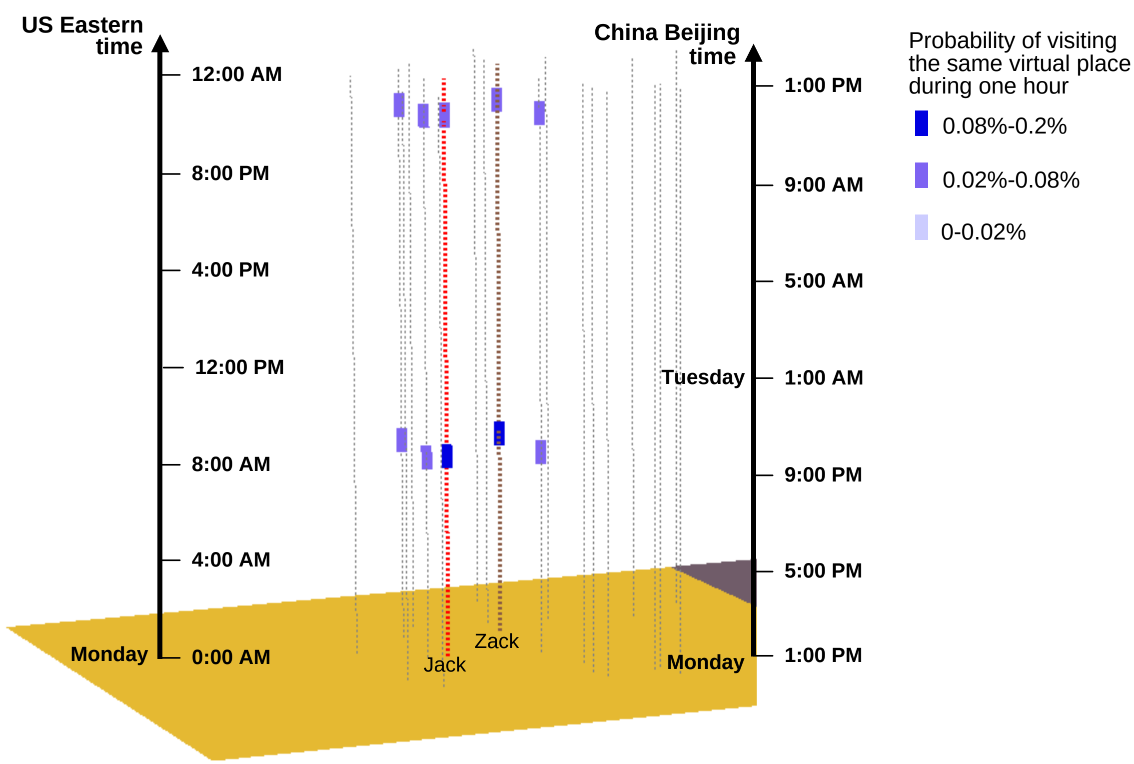



(f) Ray's space-time prisms on Saturday in US Eastern Time

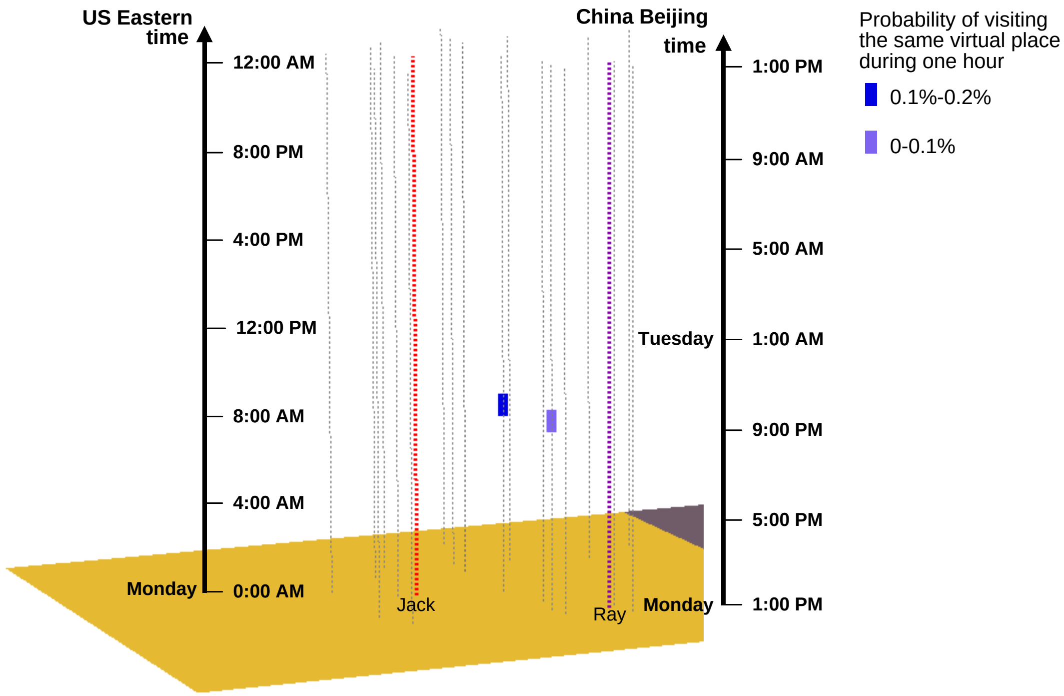
Figure 4.27 Four selected individuals' space-time prisms on selected day of week



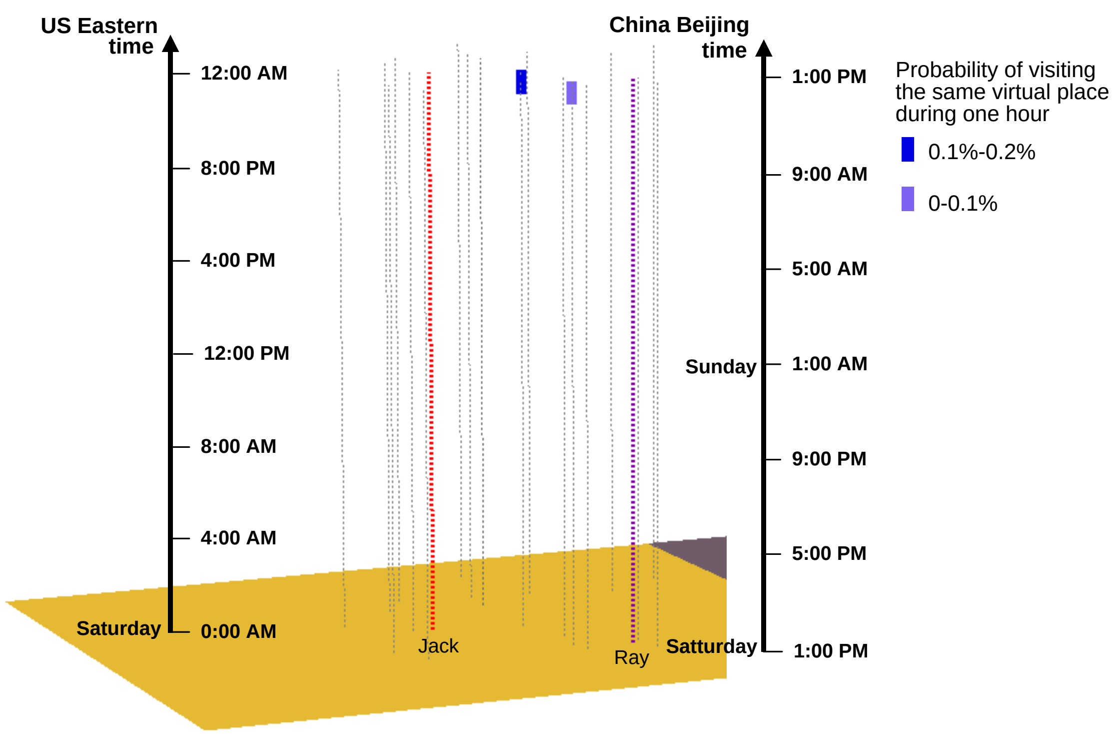

(a) Synchronous interaction probabilities between Jack and Brad on Monday in US Eastern Time




(b) Synchronous interaction probabilities between Jack and Zack on Monday in US Eastern Time




(c) Synchronous interaction probabilities between Jack and Ray on Monday in US Eastern Time




(d) Synchronous interaction probabilities between Jack and Ray on Saturday in US Eastern Time

Figure 4.28 Synchronous interaction probabilities in selected scenarios

The examples above demonstrate the way that different constraints limit people's activities and interactions in virtual space. As physical space-time prisms can help us understand and explore people's movement patterns in the geographical space, virtual space-time prisms offer an analytical and visualization approach to help us understand and predict people's activities and interactions in virtual space.

## 4.6 Summary

Current time-geographical analytical frameworks allow us to represent and analyze individuals' movements and their interactions under different constraints in the physical world. This study is the first to migrate several important concepts of classical time-geography from physical space to virtual space, particularly an online social network space. The revisited concepts applied to virtual space include virtual place, virtual movement, constraints on virtual activities, virtual space-time path, virtual space-time prism, and probabilistic virtual space-time prism (Table 4.6). With these revisited concepts, this study developed a conceptual and analytical framework for representing and analyzing individuals' movements and interactions under constraints in virtual space. Multi-representation is used through the analytical framework. These concepts in virtual space are represented based upon geographical maps and social networking graphs; moreover, the novel concept of social space-time path is presented to develop the representation based on social networking graphs. People' social space-time paths depicting their relative positions in a social network over time also offer a new representation of dynamic social networks.

Table 4.6 Time geography concepts migrated from physical space to virtual space in this study

| Time geography concepts in physical space | | Extended time geography concepts in virtual space |
|---|---|---|
| physical place | → | virtual place |
| physical movement | → | virtual movement |
| constraints on activities | → | constraints on virtual activities |
| space-time path | → | virtual space-time path |
| space-time prism | → | virtual space-time prism/ virtual probabilistic space-time prism |

Four tools are developed under the VBA environment in ArcGIS 9.3 to implement the extended time-geographical analytical framework. The virtual space-time path generator can create virtual space-time paths for the two representation methods. The social space-time path generator provides a user-customizable interface to create social space-time paths based on user need. The cluster analysis tool can conduct hierarchical clustering and *k*-medoids clustering for any type of space-time paths based on a certain similarity measurement and create generalized space-time paths based on identified clusters for group trend analysis. The virtual space-time prism analysis tool can calculate an individual's virtual probabilistic space-time prisms on a selected day of the week and analyze synchronous interaction probabilities in virtual space for two people during a day.

This study collected data from 37 participants who graduated during the last six years from the same department at a university, and who were scattered around the world. The data included their communication records on several of the most commonly used social networking websites and their residence history during the same six years.

The participants' virtual space-time paths in both two representations validated the hypothetical movement patterns in virtual space. The two representations of virtual space-time paths demonstrated their advantages and limitations in terms of visualizing different meanings of distance and location, capacity for handling a large data set, and sensitivity to spatial scale and temporal scale. The cluster analysis based on the participants' social space-time paths proved the ability of the new method for investigating dynamic social networks produced by social space-time paths. Finally, the scenario analysis based on virtual space-time prisms corroborated the two types of constraints on individuals' activities and interactions in virtual space.

# CHAPTER 5 THE IMPACT OF PHYISCAL PROXIMITY ON VIRTUAL INTERACTIONS

As the barriers to human interactions in physical space have been significantly removed in virtual space, a fundamental question for researchers has surfaced: Does physical distance still matter for social connections in the ICT age? Knowles (2006) pointed out that physical location remains all-important as time/space relationships collapse differentially over space. Recent studies have analyzed online communication data and determined that a positive association exists between geographical proximity and friendship probability in online communities, as well as between geographical proximity and virtual communication frequency (Liben-Nowell *et al*. 2005; Mok *et al*. 2009; Scellato *et al*. 2010). These studies focused on examining the aggregate relationships between physical distance and virtual interactions using classical statistical analysis. The reality, however, is a dynamic process that generates the observed aggregate patterns. There are few studies investigating the dynamic relationships between physical proximity change and virtual closeness change by analyzing online communication data and physical movement data together. For example, how does physical migration affect people's social closeness in virtual space? How can we analyze online communication data and physical movement data in order to answer the above question? Such research needs a spatio-temporal analysis environment, which is able to visualize, compare, and analyze the changes in both physical distance and virtual closeness.

This chapter proposes specific spatio-temporal exploratory approaches to investigating and understanding the relationship between physical distance change and virtual closeness change. It also implements these approaches in a space-time GIS. The space-time GIS offers a spatio-temporal exploratory environment for researchers to study the changes of physical distance and virtual closeness over time within a single analysis environment.

Although ICT permit instantaneous communication over distance, people have to deal with time zones and work/sleep cycles. The association between temporal proximity—time zone difference—and communication time-lag in virtual space is another indication of the impact of physical distance on virtual interactions. However, this association was not examined in a spatio-temporal exploratory environment, nor represented at the individual level in current literature (Herbsleb *et al*., 2001; Espinosa *et al*., 2007; Nguyen *et al*., 2008; Ohira *et al*., 2010). Virtual space-time prisms are able to reveal the impact at the individual level within a spatio-temporal environment, thus they are part of the spatio-temporal exploratory environment.

In order to examine the relationships between spatio-temporal proximity and virtual interactions, classical statistical methods such as Student *t*-test, ANOVA, and regression analysis are useful to explore aggregate patterns. The presented spatio-temporal exploratory environment is able to complement classical statistical environments with better spatio-temporal visualization capabilities and specialized analysis functions for spatio-temporal data. This study presents a case study to demonstrate the feasibility and effectiveness of integrating the two environments to address the relationships between spatio-temporal proximity and virtual interactions.

This chapter first discusses the spatio-temporal approaches for exploring dynamic relationships between physical proximity and virtual closeness over time, as well as in the spatio-temporal exploratory environment. Then it applies the approaches and the environment in a case study to demonstrate how they complement classical statistical analysis. Finally, it ends with a summary and a discussion about the contributions of this chapter.

## 5.1 A Spatio-temporal Exploratory Environment

### *5.1.1 Virtual closeness changes with physical proximity changes between two people*

In order to investigate virtual closeness change with physical proximity change between two people, the two changes must be compared. As discussed in Chapter 4, physical space-time paths visualize individuals' movements across the physical space. Figure 5.1a depicts two persons' physical space-time paths, from which we can observe their physical location changes over time; their physical proximity change yet is not directly visualized. The counterpart of an individual's physical space-time path in virtual space is his/her virtual space-time path. Figure 5.1b shows the two persons' virtual space-time paths based on their geographical locations. By representing each visit made by an individual's in a SNS space, a virtual space-time path includes that person's interactions with all his/her friends. Two persons' virtual space-time paths together visualize two persons' interactions with all friends, instead of focusing on the interactions between the two of them. It is not easy to identify their interactions from the cluttered paths (Figure 5.1b), particularly if they are active in the SNS space. In addition, although interaction frequency between two people can reflect interpersonal closeness, sometimes observing the interaction frequency from two virtual space-time paths is not straightforward. Social space-time paths are generated based upon virtual closeness among the members of a group. Two individual's social space-time paths respectively represent their position changes within the entire social group. Thus, the relationship between two persons' social space-time paths does not guarantee an accurate description of their social closeness change. For instance, in Figure 5.1c, Guia moved toward to the center of the entire social network, while Nina always stayed in the fringe area, but this pattern does not necessarily mean they became distant over time. Although Guia contacted more friends in recent years, she might be still the one who interacted with Nina the most. The spatio-temporal exploratory approaches presented in Chapter 4 have some limitations in examining the virtual closeness change with physical proximity change between two people. This section therefore presents another approach to facilitate investigating the association between physical proximity change and virtual closeness change.

This study proposes a pair of charts for graphic examination based on the dynamics of the two aspects of interest. Given an ego (an individual of interest), a *relative physical distance chart* depicts the ego's friends' physical distance change over time relative to the ego. It is another form of individuals' physical space-time paths. As Figure 5.2a demonstrates, the horizontal axis of a relative physical distance chart refers to the physical distance of a friend relative to the ego, while the vertical axis represents time. The measurements of physical distance depend on the need or interest of applications. The left vertical line stands for the ego person. To the right of the ego line, each line represents a friend. The example in Figure 5.2a shows that the ego and the friend were far apart, and then moved closer at a time point. The relative distance however does not show who moved or which place they moved from or to. Thus, a relative physical distance chart and physical space-time paths can complement each other. A *virtual closeness rank chart*, on the other hand, traces an ego's friends' virtual closeness rank change over time among the ego's all friends. The horizontal axis refers to virtual closeness rank in a descending order from left to right (Figure 5.2b), with *n* representing the total number of the ego's friends during the study period. The farthest end of the axis stands for no connection at all. The measurement of interpersonal closeness varies by applications. The left vertical line also stands for the ego person, and a line right to it represents a friend. As Figure 5.2b shows, the friend did not communicate with the ego in virtual space at the beginning, and gradually this person became a close friend of the ego in virtual space. When the two charts are viewed together, it is easy to observe the association between physical proximity change and virtual closeness change for a pair of individuals over time. In the example of Figure 5.2, after the two people moved closer in physical space, they became closer in virtual space as well. This indicates a positive association between physical proximity and virtual closeness. Moreover, the two charts make it possible to represent all friends of an ego with multiple lines.

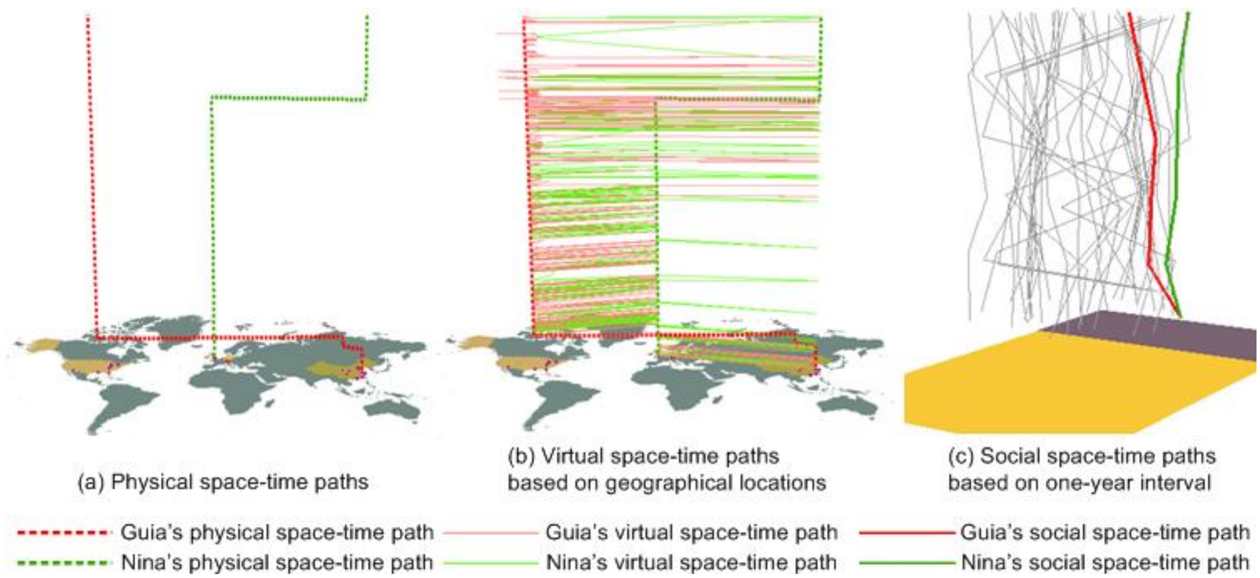



Figure 5.1 Comparison between physical proximity change and virtual interaction change by presented spatio-temporal exploratory approaches in Chapter 4

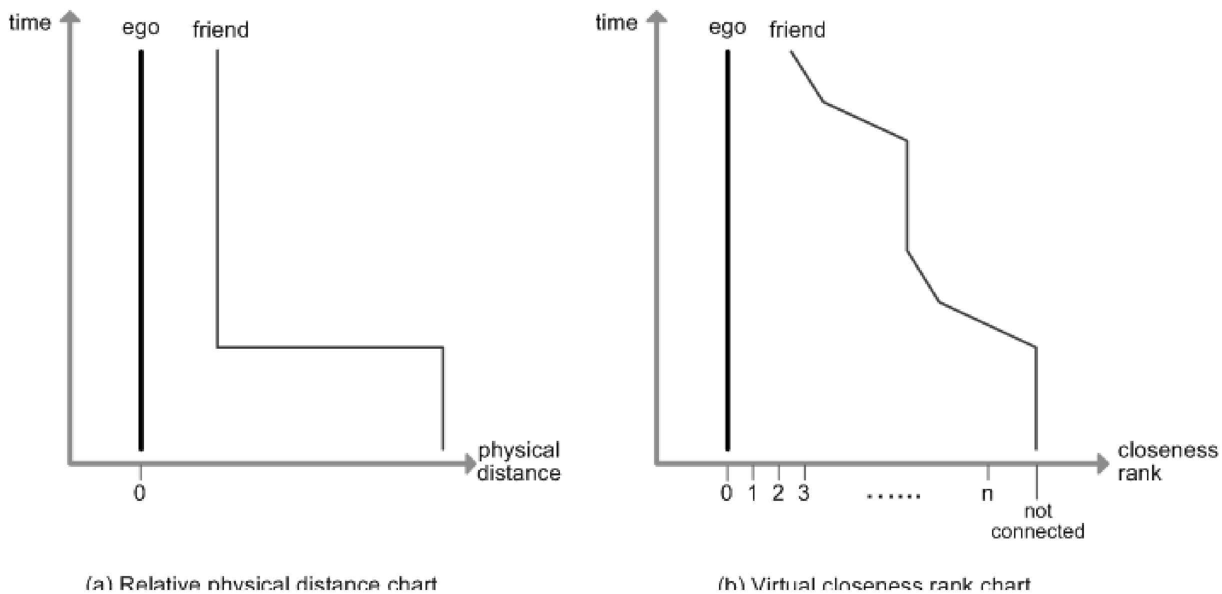



Figure 5.2 Relative physical distance chart and closeness rank chart

### *5.1.2 Patterns of virtual closeness changes with physical proximity changes among a group*

The exploratory approach presented in the last section has focused on a pair of people. As ICT expanded the flexibility of developing and maintaining social ties, the relationships between physical proximity and virtual closeness might exhibit various patterns. How can we identify different relationships between virtual closeness changes and physical proximity changes among the members of a group? In other words, how can we identify pairs of people with similar virtual closeness change over physical distance change? This section presents a 3D cluster approach to visualize and identify different relationships. The three axes in a 3D coordinate system represent virtual closeness, physical distance, and time respectively. A 3D line within this coordinate system represents two individuals' virtual closeness changes over time, as well as their physical distance changes over time. Twelve typical patterns of virtual closeness changes with physical distance changes are presented in Table 5.1 and Figure 5.3. A real world pattern could be a combination of several typical patterns; for instance, two people's physical distance may increase first and then decrease, or their virtual closeness may increase first and then decrease. In general, if some pairs of people have similar patterns, their 3D lines should have similar shapes and locations in the 3D coordinate system. Chapter 4 discussed the similarity measurements of two 3D lines and demonstrated the cluster analysis based on the similarity measurements. This chapter will apply the same similarity measurement and the same cluster analysis approaches to the 3D lines.

Table 5.1 Twelve typical patterns of virtual closeness change with physical distance change

| Pattern | Initial status of SNS closeness | Physical distance change | Virtual closeness change |
|---|---|---|---|
| Pattern 1 | Far | No change | No change |
| Pattern 2 | Far | No change | Become close |
| Pattern 3 | Far | Decrease | No change |
| Pattern 4 | Far | Decrease | Become close |
| Pattern 5 | Far | Increase | No change |
| Pattern 6 | Far | Increase | Become close |
| Pattern 7 | Close | No change | No change |
| Pattern 8 | Close | No change | Become far |
| Pattern 9 | Close | Decrease | No change |
| Pattern 10 | Close | Decrease | Become far |
| Pattern 11 | Close | Increase | No change |
| Pattern 12 | Close | Increase | Become far |

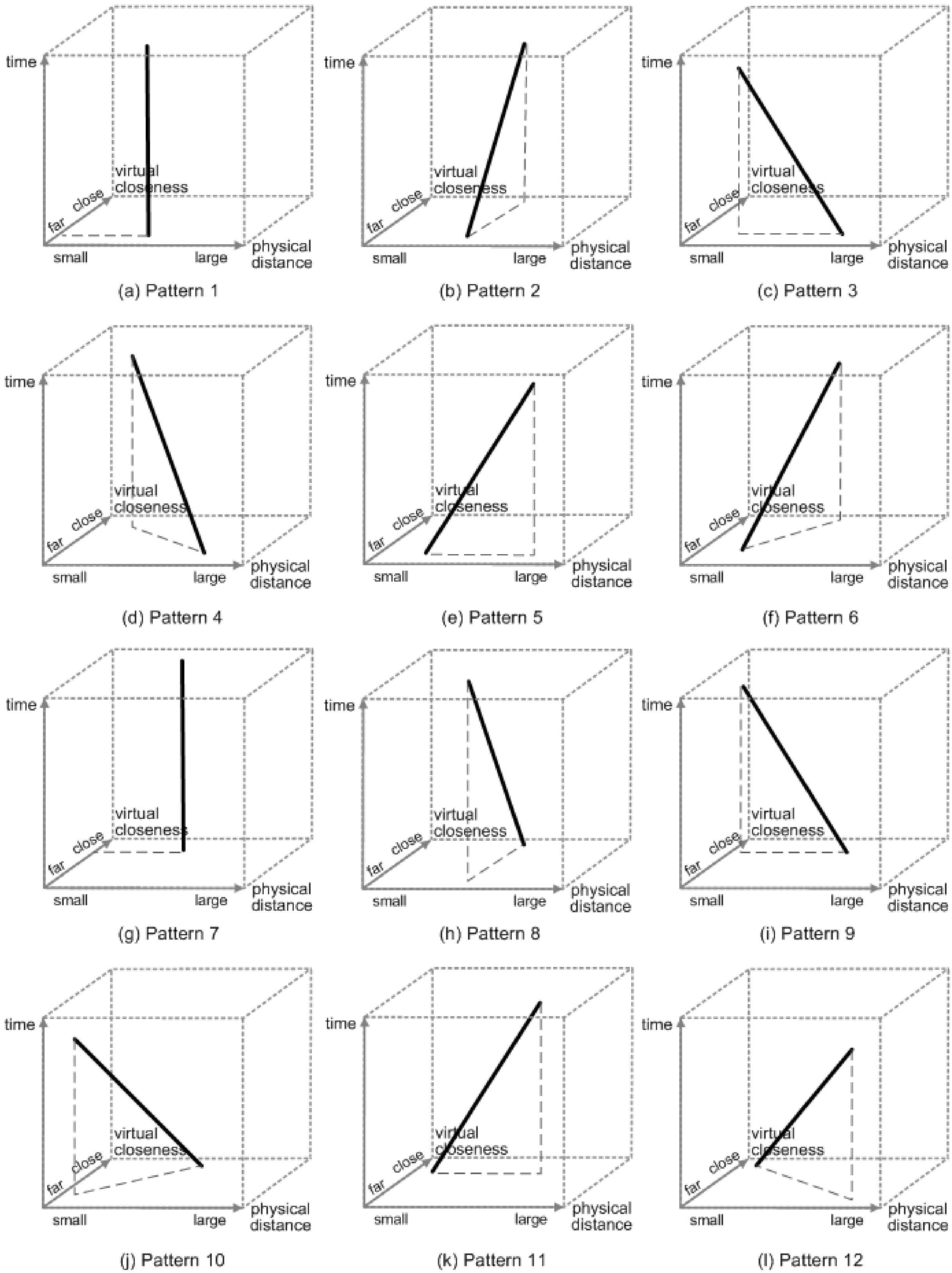



Figure 5.3 Twelve typical patterns of virtual closeness change with physical distance change

### *5.1.3 A spatio-temporal exploratory environment*

The spatio-temporal exploratory tools presented in Chapters 4 and 5 complement one another, and together they form an analysis environment for exploring human interactions in virtual space and their associations with physical spatio-temporal proximity (Figure 5.4). Physical space-time paths depict individuals' physical movements within a geographical context. Researchers can also observe interpersonal physical proximity change from their physical space-time paths. In the meantime, these individuals' virtual locations can be represented by either their physical locations or relative locations within a social network. Based on their virtual locations, their virtual interactions can be represented by virtual space-time paths. Their social space-time paths also can attach information about their social closeness relationships and subgroup identities. With a group of physical space-time paths, virtual space-time paths, and social space-time paths, researchers can observe how these people travel across the physical world; they can also observe how the subjects interact with others in the virtual world, and how they move within the social network over time.

A relative physical distance chart and a virtual closeness rank chart offer a finer observation lens when focusing on a particular person's relationships with other friends in both physical and virtual spaces. A relative physical distance chart is derived from physical space-time paths, and a virtual closeness rank chart is derived from social closeness matrices that are also the basis of social space-time paths. A relative physical distance chart and a virtual closeness rank chart together show the physical proximity change and virtual closeness change, which may indicate relationships between the two changes.

At the aggregate level, 3D cluster analysis allows exploring different patterns of relationships between physical proximity change and virtual closeness change in a group of people. Each pair of people has a 3D line, and it could be clustered with other people's 3D lines of similar patterns.

The exploratory approaches discussed above concentrate on people's physical movements, virtual movements, and their relationships. Virtual space-time prisms, alternatively, reveal an individual's activity time and interaction probability in virtual space. Virtual space-time prisms can analyze and visualize interaction time windows between people with time zone differences. It explores the impact of temporal distance on human interaction in virtual space at the individual level.

In summary, these spatio-temporal exploratory analyses are implemented in a space-time GIS. The rest of the chapter demonstrates how this exploratory environment can facilitate relevant research.

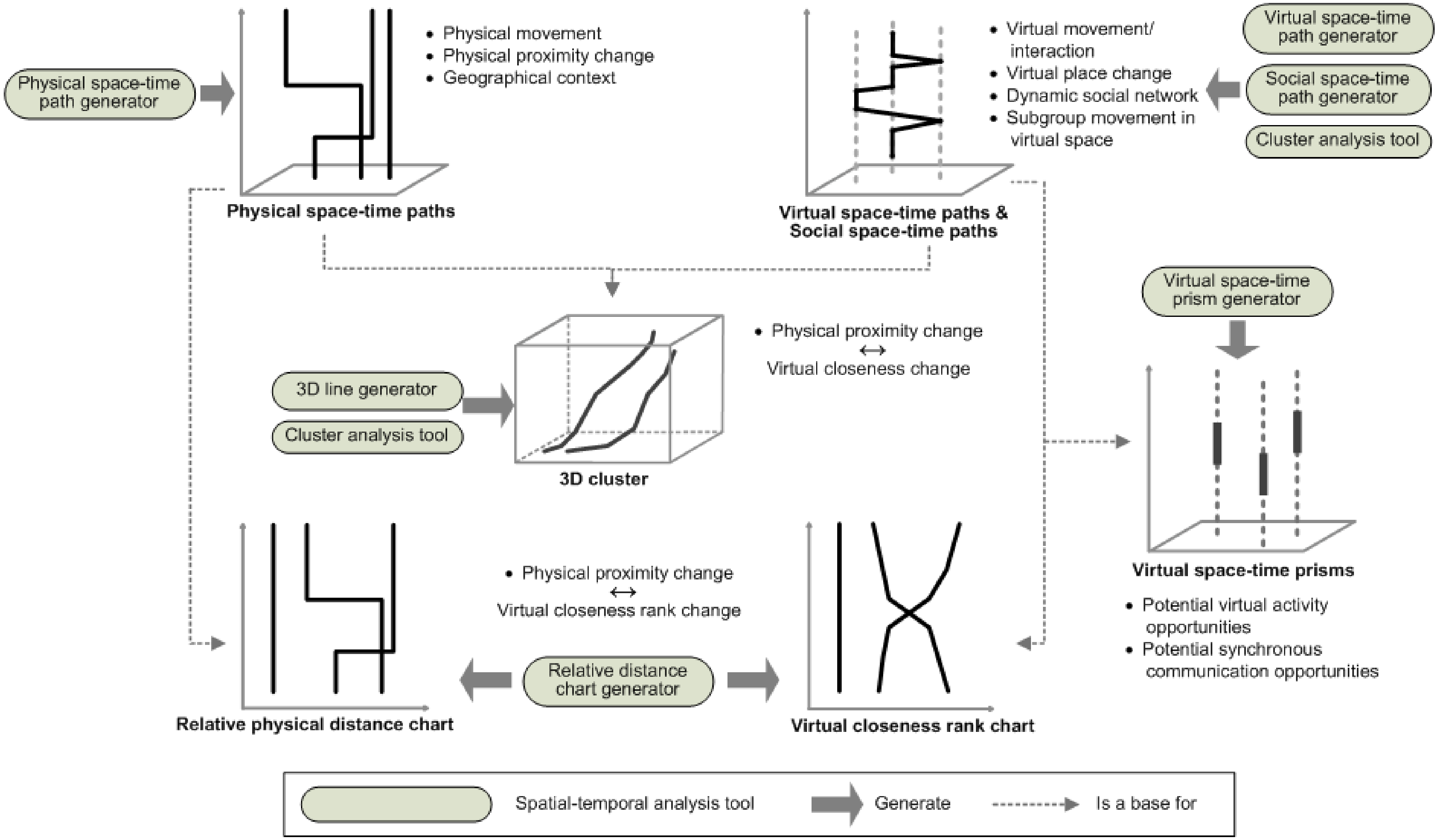



Figure 5.4 A spatial-temporal exploratory environment for examining human interactions in virtual space and their associations with physical spatio-temporal proximity

## 5.2 Data Description

A case study was conducted to examine the relationships between physical proximity and social closeness for participants in their SNS spaces. It also analyzed the effect of time zone differences on communication time-lag in the SNS space. This case study used the same dataset described in Chapter 4. The basic information of the 37 participants is summarized in Table 5.2. The dataset includes their communication records in their three major social networking websites, their residence history, and their ICT habits in maintaining social networks. Chapter 4 has described the communication records and residence history data; this section analyzes participants' self-reported SNS habits.

Table 5.2 Participants' basic information

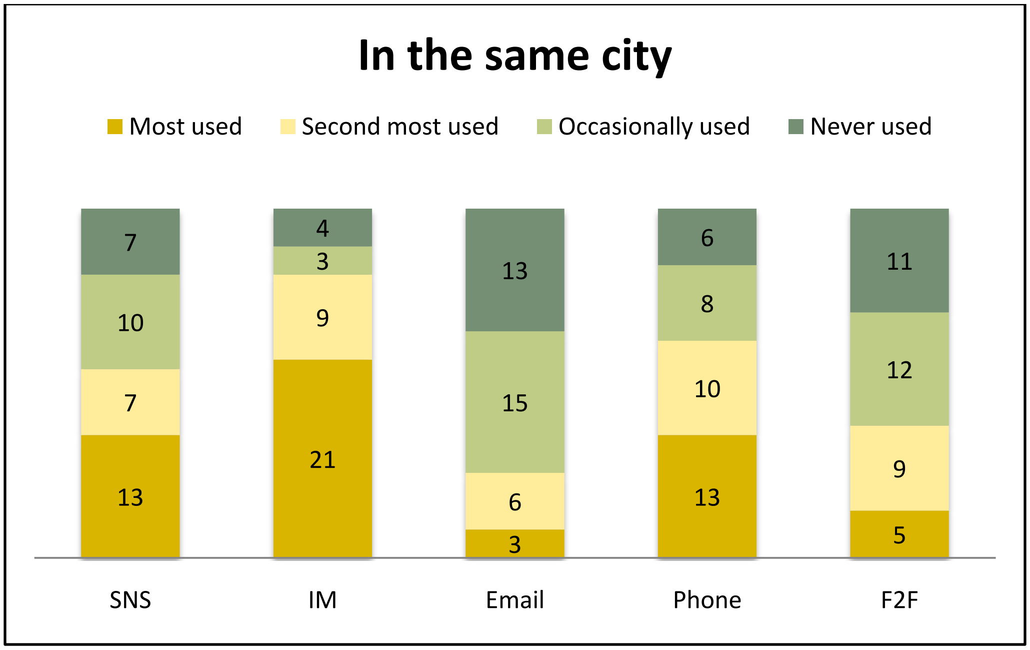
| Item | | Number of participants | Percentage of participants |
|---|---|---|---|
| Gender | Female | 17 | 45.95% |
| | Male | 20 | 54.05% |
| Age | 25-30 | 31 | 83.78% |
| | 30-35 | 5 | 13.51% |
| | 35-40 | 1 | 2.71% |
| Occupation | Working | 29 | 78.38% |
| | Student | 8 | 21.62% |
| Years at Nanjing University | 0-4 | 9 | 24.32% |
| | 4-7 | 19 | 51.36% |
| | >7 | 9 | 24.32% |
| Graduation year[a] | 2003 | 3 | 8.11% |
| | 2004 | 2 | 5.40% |
| | 2005 | 6 | 16.22% |
| | 2006 | 15 | 40.53% |
| | 2007 | 10 | 27.03% |
| | 2008 | 1 | 2.71% |

(a: The graduation year refers to the graduation year of their last degree at Nanjing University if they pursued more than one degree. )

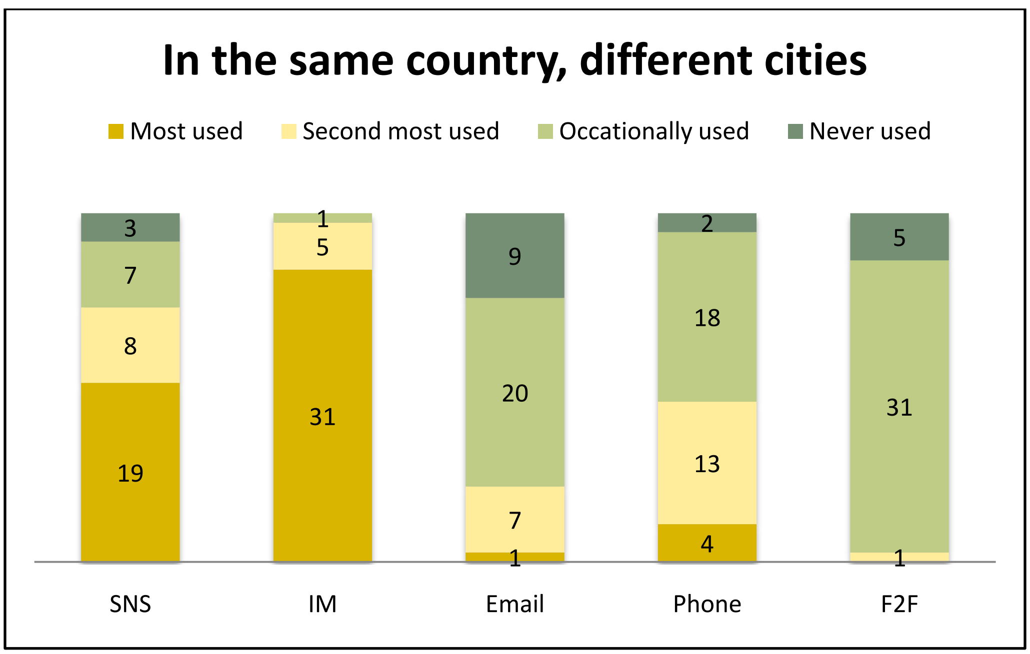
This study's survey examined the participants' different communication habits in contacting classmates over different levels of physical distance after graduation (Appendix B). Optional communication means included social networking services (SNS), instant messaging (IM), email, phone, and face-to-face meetings (F2F). Optional usage habits include "most used," "second most used," "occasionally used," and "never used." This information can help account for the analysis results gleaned from SNS communication data.

As expected, the frequencies of F2F and phone contact sharply decreased when physical distance increased from "in the same city" to " in different cities" and almost disappeared for classmates in other countries (Figure 5.5). This pattern matched the previous findings of Boase *et al*. (2006) and Tillema *et al*. (2007). Overall, the participants in this study are not frequent email users. The communication methods most used for more than half of them were SNS and IM for all levels of physical distance. Moreover, the survey also covered participants' purposes for using SNS (Appendix B). The primary reasons for using SNS indicated by the participants included posting their own status, checking friends' updates, and having casual conversation with friends, all of which are activities important in maintaining friendships (Figure 5.6).

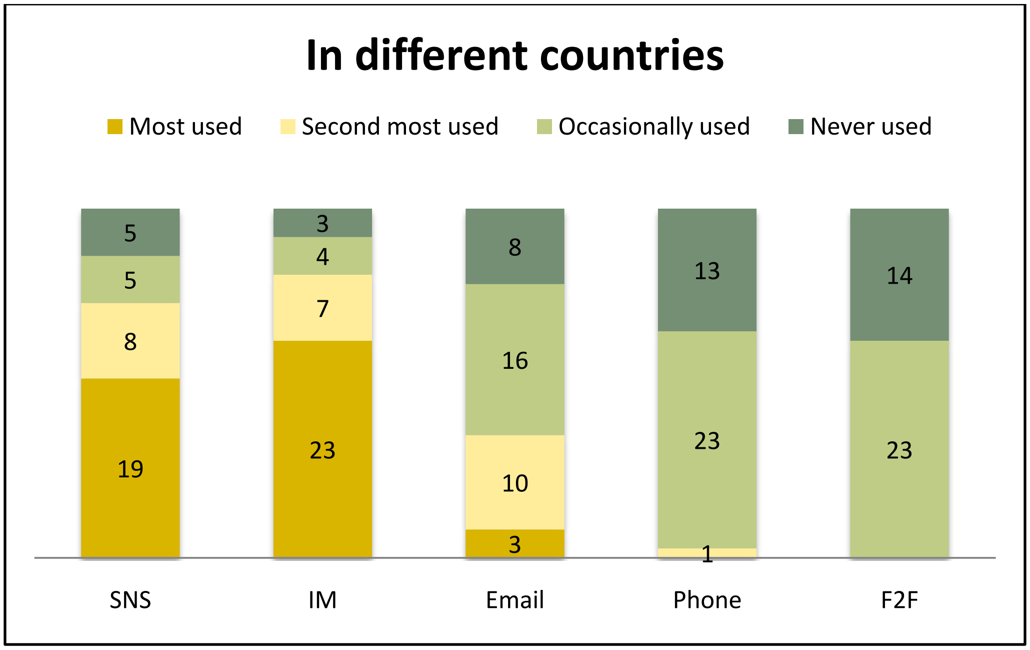
Due to the important role of SNS in maintaining friendships among the participants, their SNS closeness could be an effective reflection of their real relationships. The discoveries from the SNS space thus could indicate the actual relationships of the participants.




(a) Different means to communicate with alumni in the same city




(b) Different means to communicate with alumni in different cities but still within the same country




(c) Different means to communicate with alumni in different countries

Figure 5.5 Participants' habits of using different communication means to contact with alumni after graduation

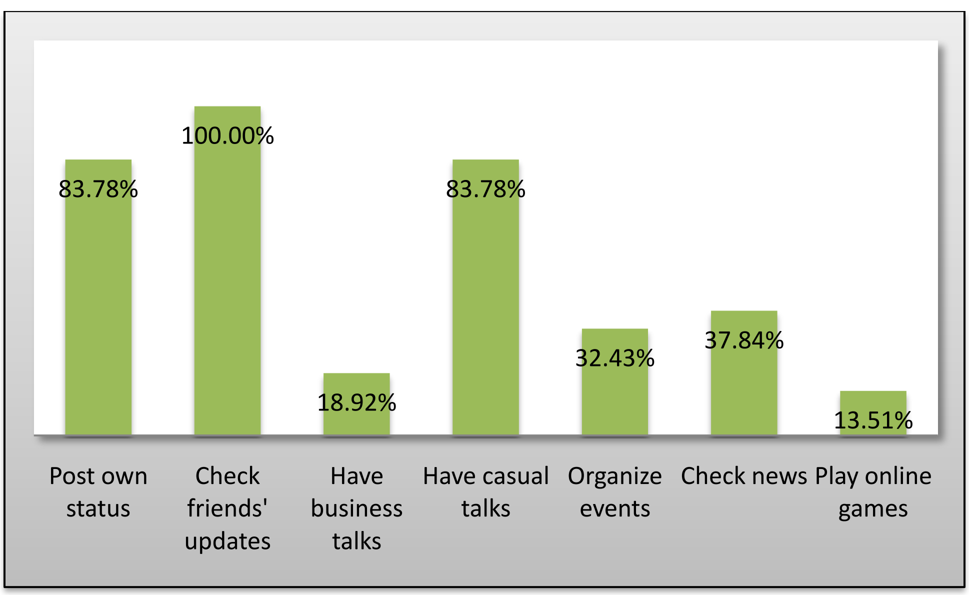



Figure 5.6 Participants' purposes of using SNS

## 5.3 The Analysis Design of the Case Study

Classical statistical analysis and the spatio-temporal exploratory environment have their own focuses and advantages. The case study conducted analysis in both environments in order to construct a comprehensive picture of the relationships between spatio-temporal proximity and virtual interactions for the participants. The case study is organized as depicted in Figure 5.7. First, an analysis tool in the space-time GIS creates variables to measure physical proximity, virtual closeness, temporal proximity, and communication time-lag of each online conversation. Statistical tools, such as *t*-test, ANOVA, correlation analysis, and regression analysis are applied to investigate the aggregate relationship between physical proximity and virtual closeness among all pairs of participants. On the other hand, the spatio-temporal exploratory tools are used to examine the dynamic process of virtual closeness changes with physical proximity changes for each pair of individuals. A 3D cluster analysis is used to identify different patterns in the dynamic process. Relative distance charts of physical distance and of virtual closeness rank can help account for the dynamic process for a particular pair of people or a particular person's relationships with others in both physical and virtual spaces. In terms of examining the impact of temporal distance on virtual interaction promptness, statistical tools can analyze the aggregate relationship between temporal proximity and communication time-lag. In order to observe such relationship at the individual level, virtual space-time prisms offer visualization and analysis tools for exploring individual interaction time windows in virtual space.

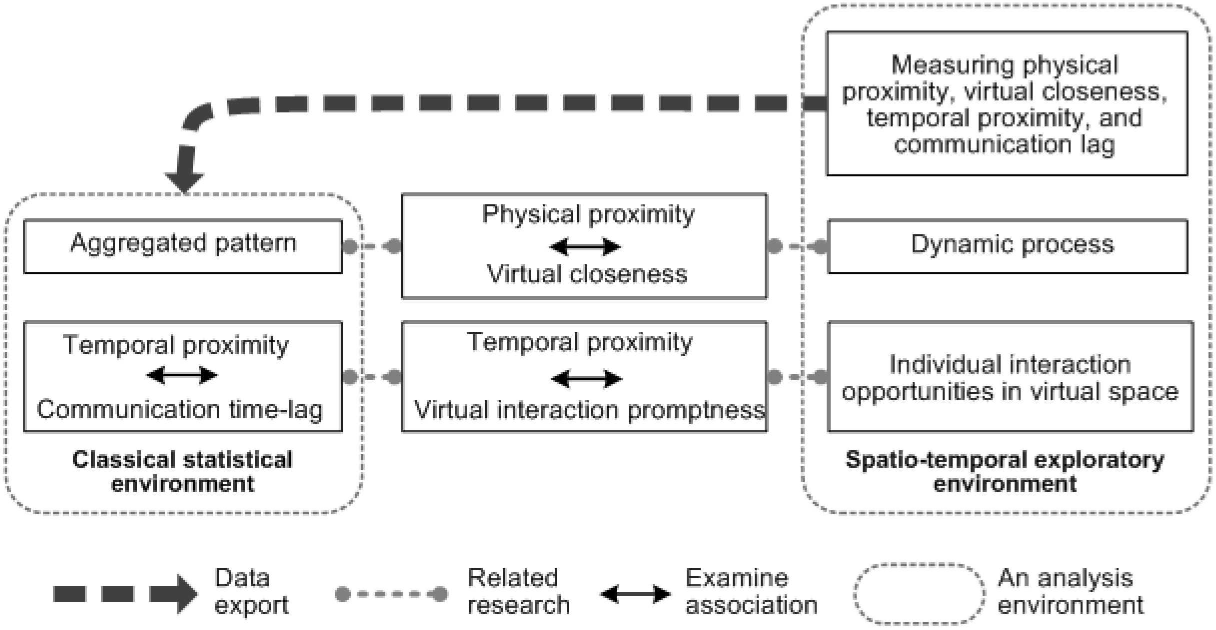



Figure 5.7 The research design of the case study

## 5.4 Case Study

### *5.4.1 Measurements of physical proximity and virtual closeness*

This study uses two approaches to measure physical proximity. The first approach is based upon geographical distance on the surface of the earth. Given a time moment, the great circle distance between two individuals' physical locations is their physical proximity at that time moment. Individuals move across physical space over time. Two individuals' physical proximity within a given time period is measured by their average physical proximity over the time period. The physical movement data of participants in this study is their residence history, which is accurate at the city level on a daily basis. The overall average geographical distance $D1$ for a pair of people during a time period is:

$$D1 = \frac{\sum_{t=1}^{n}(GCD(x_i^t, y_i^t, x_j^t, y_j^t)}{n} \qquad (5\text{-}1)$$

where

$(x_i^t, y_i^t)$ are individual *i*'s geographical coordinates on the *t*th day;

$(x_j^t, y_j^t)$ are individual *j*'s geographical coordinates on the *t*th day;

$GCD(x_i^t, y_i^t, x_j^t, y_j^t)$ is the great circle distance between individual *i* and *j* on the *t*th day;

*n* is the total number of days during the time period.

The other measurement of physical distance considers both physical and social context of a location. At a given time moment, it uses numbers 1 through 6 to represent six hierarchical categories in an ascending order of physical distance: 1- in the same city; 2- in the same region (<500 km); 3- in the same country; 4- in the same continent; 5- between major continents (e.g., between China and Europe, between Europe and the U.S.); 6- on the opposite point on the earth (e.g., between China and the U.S.). Similar to the first approach, the overall average categorical distance *D*2 for each pair of people during a time period is:

$$D2 = \frac{\sum_{t=1}^{n}(CD(x_i^t, y_i^t, x_j^t, y_j^t)}{n} \tag{5-2}$$

where

$CD(x_i^t, y_i^t, x_j^t, y_j^t)$ is the categorical distance between individual *i* and *j* on the *t*th day.

Note that the physical distance index *D*2 can be treated as a continuous variable after an average operation. Yet, it is based on a categorical measurement, and its interpretation is not always straightforward. For example, two persons were living in the same city in China during the first three years, and one moved to the U.S. in the last three years. On average, their physical distance index *D*2 for the six years is 3.5. Understanding this value of 3.5 requires knowledge of the entire migration history of the two persons. The physical distance index *D*2 only represents an index of average physical distance over a time period. The differences and ratios between physical distance indexes can only represent a relative relationship. For example, if comparing an index of 4.0 for person A and person B and an index of 2.0 for person C and person D, we can only conclude that the average categorical distance between person A and person B is larger than it is between person C and person D.

Chapter 4 uses communication count and visit probability to define virtual distance between people (see Section 4.5.3). This chapter defines two measurements for virtual closeness based on communication count and visit probability. The virtual closeness index *C*1 between a pair of people based on communication counts is:

$$C1 = C(i \to j) + C(j \to i) \tag{5-3}$$

where

$C(i \to j)$ is the total frequency individual *i* visits individual *j* in an SNS space;

$C(j \to i)$ is the total frequency individual *j* visits individual *i* in an SNS space.

The closeness index *C*2 between a pair of people based on visit probability is:

$$C2 = \left(\frac{C(i \to j)}{\sum_{j=1}^{n} C(i \to j)} + \frac{C(j \to i)}{\sum_{i=1}^{m} C(j \to i)}\right) / 2 \tag{5-4}$$

where

$n$ is the total number of individual *i*'s friends in an SNS space;

$m$ is the total number of individual *j*'s friends in an SNS space.

As Section 4.5.3 discussed, these two measurements characterize themselves by their additive process. They treat a relationship as two persons' total contributions. For instance, if the visit probabilities from A to B and from B to A are both 0.3, their closeness index based on visit probability is 0.3. If the visit probability from A to B is 0.6, while from B to A is 0, their closeness index is still 0.3.

A tool is developed to generate variables measuring physical proximity, virtual closeness, temporal proximity, and communication time-lag (Figure 5.8). The input files of this tool include physical migration table, virtual communication table, individual information table, and the feature class of individuals' physical space-time paths. The parameter of time interval sets the time frame for these measurements. For example, setting "6 years" time interval will generate average physical proximity and virtual closeness over a period of six years, while setting "1 year" time interval will generate the two variables for each year. The parameters of distance measurement and communication measurement allow users to choose a particular type of measurement for each variable.

There were 666 pairs of people among 37 participants in the dataset; 249 pairs left recordable communication activities in the SNS space during the entire study period. The pairs which never left a message for each other were excluded from this study. Figure 5.9 to Figure 5.12 exhibit the distribution of the four variables for the 249 pairs of participants over the six-year period.

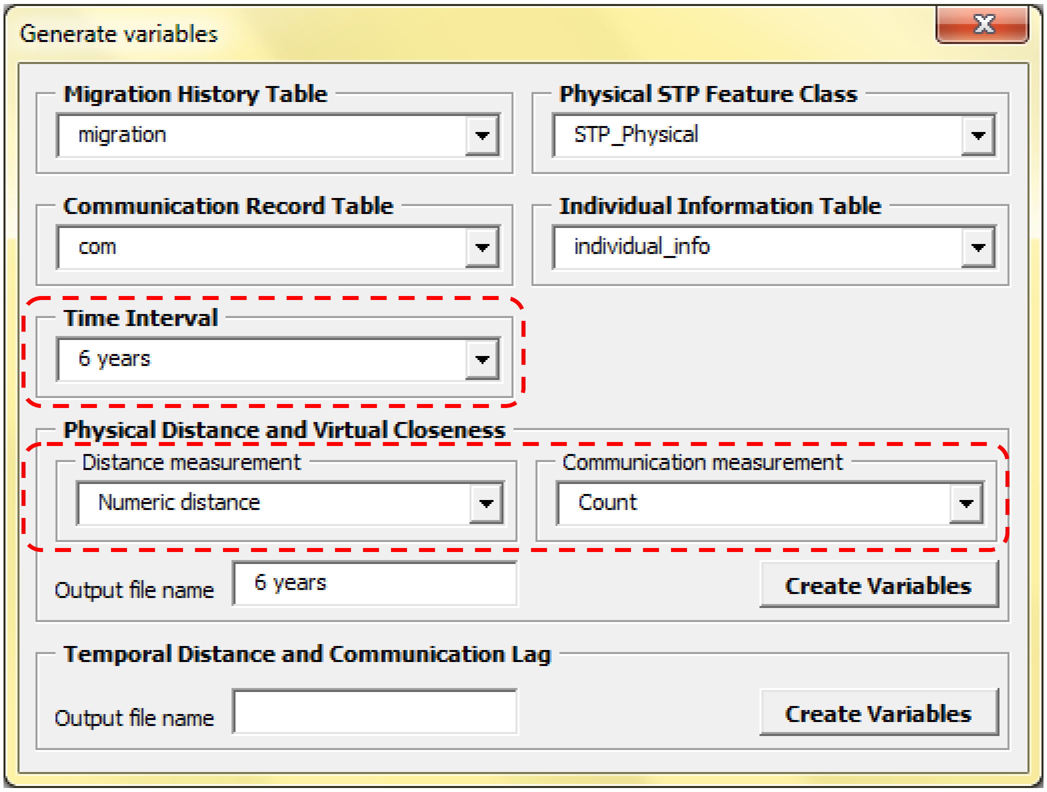



Figure 5.8 The Tool to generate variables measuring physical proximity, virtual closeness, temporal proximity, and communication time-lag

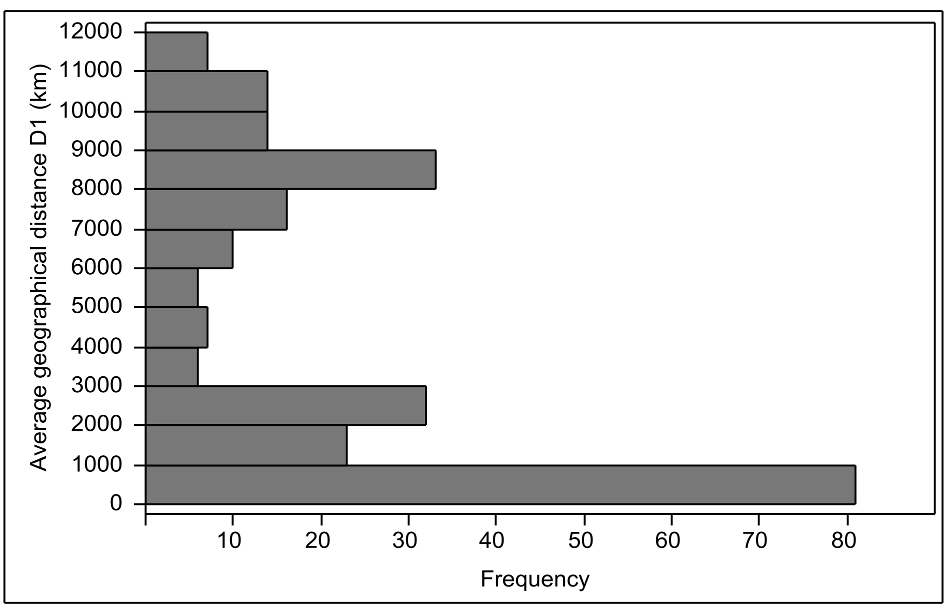



Figure 5.9 The histogram of average geographical distance *D*1 in the entire study period

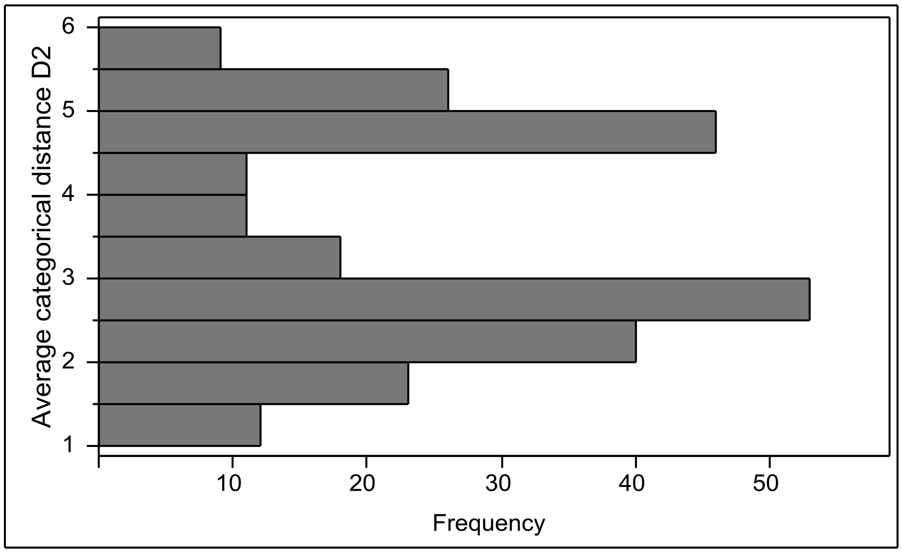



Figure 5.10 The histogram of average categorical distance *D*2 in the entire study period

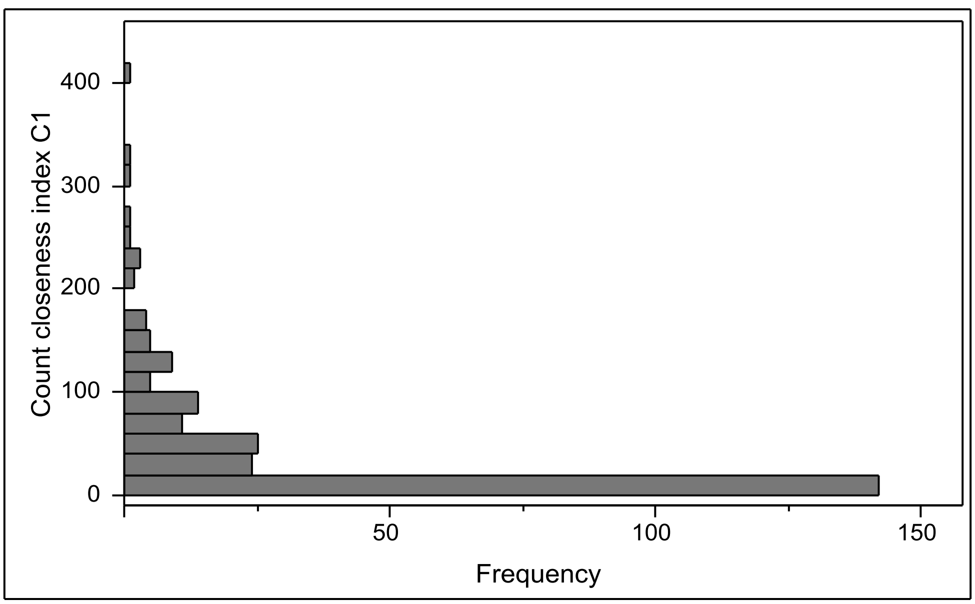



Figure 5.11 The histogram of SNS closeness index *C*1 based on communication counts in the entire study period

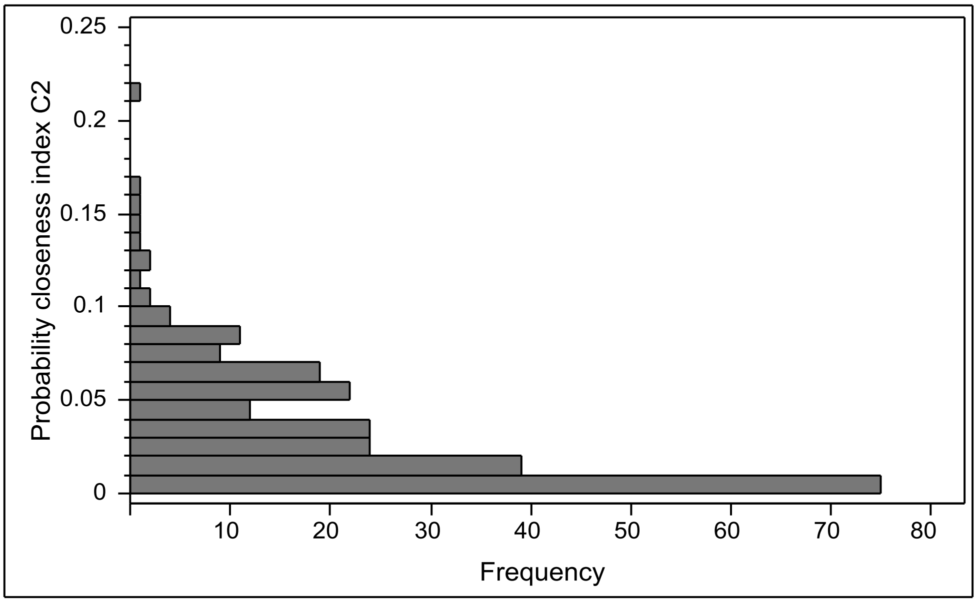



Figure 5.12 The histogram of SNS closeness index *C*2 based on visit probability in the entire study period

### 5.4.2 *Aggregate relationships between physical proximity and virtual closeness*

Figure 5.13 shows the scatterplot matrix of the four variables (*D*1, *D*2, *C*1, *C*2). The two physical proximity measurements have a large positive correlation coefficient (0.96). The two closeness measurements show differences, but still have a positive correlation coefficient (0.53). The four combinations between two physical distance variables and two SNS closeness variables are displayed by the four scatterplots at the bottom-left. The combination of *D*1-*C*1 represents the relationship between average geographical distance and virtual closeness based on communication counts. It illustrates two patterns: two clusters in geographical distance and the extreme skew toward small value in communication count (Figure 5.9 and Figure 5.11). The combination of *D*2-*C*2, which represents the relationship between average categorical distance and virtual closeness based on visit probability, largely erases these two patterns (Figure 5.10

and Figure 5.12). The other two combinations of *D*2-*C*1 and *D*1-*C*2 are intermediate between *D*1-*C*1 and *D*2-*C*2 in terms of the two patterns. For demonstration, this study only chose the combinations of *D*1-*C*1 and *D*2-*C*2 to conduct the following statistical experiments.

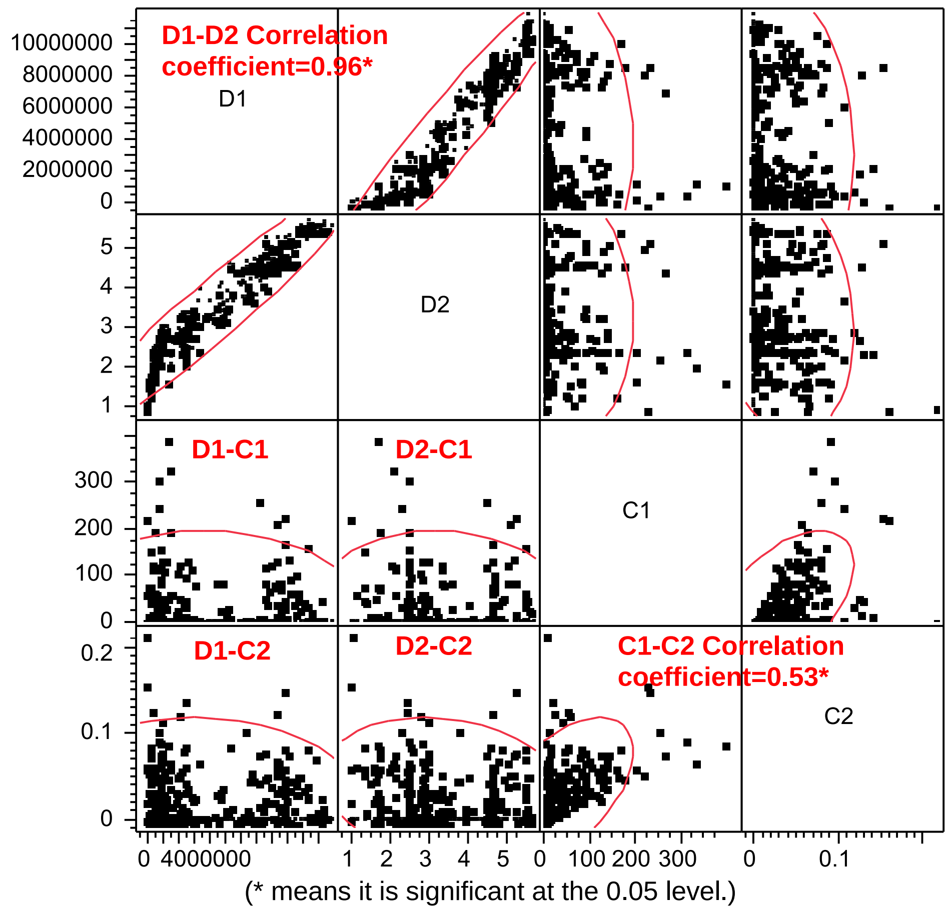



Figure 5.13 Scatterplot matrix of the four variables for physical proximity and SNS closeness

**(1) The relationship between average geographical distance and virtual closeness based on communication counts**

This study first divides average geographical distances into several groups at three scales. At the world scale, the groups of 0–4,500 km, 4,500–7,000 km, and 7,000–12,000 km respectively represent distance within the U.S., China, or Europe, distance between the U.S. and Europe or between Europe and China, and distance between the U.S. and China. At the country/continent scale, groups are created by every 500 km between 0–4,500 km, which represent different distance levels within the U.S., China, or Europe. At the regional scale, groups are created every 50 km between 0–500 km, which represent different distance levels within a region. Three ANOVA analyses were conducted to examine whether the means of communication count per pair of people in different geographical distance groups were comparable. None of the three tests yielded statistically significant results. Then three regression analyses were conducted to examine whether there was an association between communication count and average geographical distance for the entire world, the same country/continent, or the same region. Communication count is a discrete variable, and matches negative binomial distribution indicated by the distribution fit examination. Therefore, this study used a negative binomial regression model, which is a type of generalized linear regression model:

$$\log(count_{ij}) = \beta_0 + dist_{ij}\beta_1 \tag{5-5}$$

where

$count_{ij}$ is the virtual closeness based on the communication counts between individual $i$ and $j$;

$dist_{ij}$ is the average geographical distance between individuals $i$ and $j$.

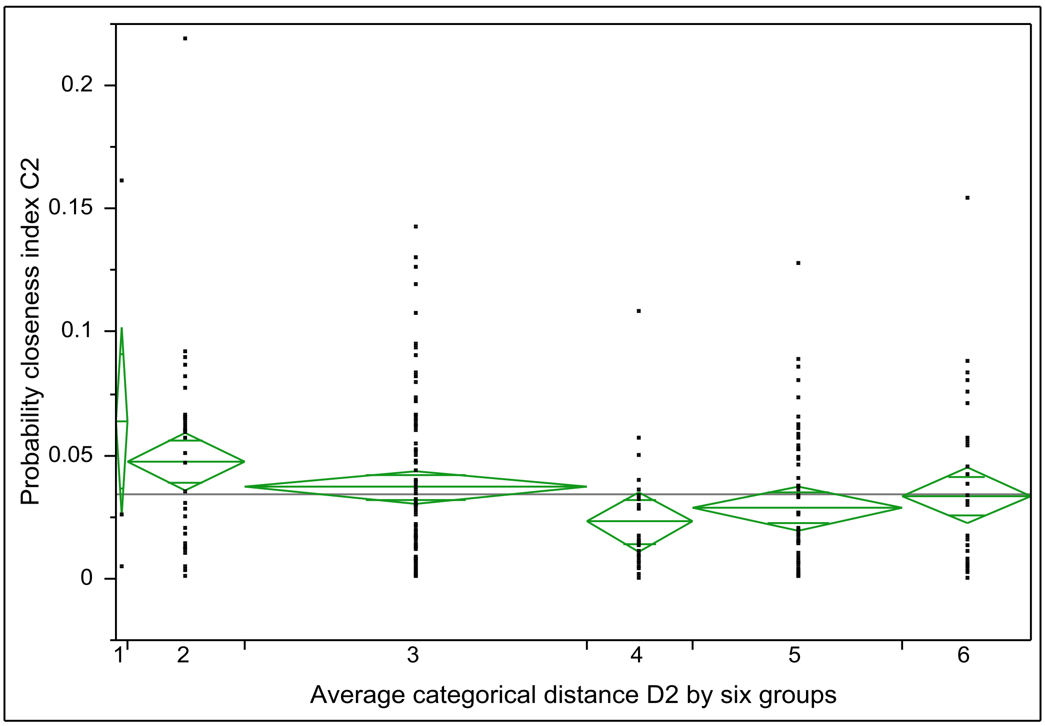
Nonetheless, none of the three regression models is statistically significant.

The statistical experiments did not suggest an association between average geographical distance and SNS closeness based on communication counts for the participants during the six years.

**(2) The relationship between average categorical distance and virtual closeness based on visit probability**

The average categorical distance is based on a categorical variable, so only ANOVA and Student’s *t*-test were used to examine its relationship with virtual closeness based on visit probability. The average categorical distance ranged from 1 to 6. Six groups of average categorical distance were used in the ANOVA: (a) Group 1: the average categorical distance equaled 1, which means both members of the pair always stayed in the same city; (b) Group 2: the average categorical distance ranged from 1–2, which means the two individuals of the pair were not always in the same city, but in generally remained in the same region; (b) Group 3: the average categorical distance ranged from 2–3, which means that the members of the pair were not always in the same region, but for the most part were still in the same country; (d) Group 4: the average categorical distance ranged from 3–4, which means the two people were not always in the same country, but on average still in the same continent; (e) Group 5: the average categorical distance ranged from 4–5, which means that the two paired people were not always in the same continent, but on average still within half the circumference of the earth (e.g., between China and Europe, between Europe and the U.S.); (f) Group 6: the average categorical distance ranged from 5–6, which means that for the most part the one of the two people was located in China and the other in the U.S. For participants who moved across the world several times, their related average categorical distances can only represent an average condition, and might not be interpreted easily.

The ANOVA result is significant at the 0.05 level (see "Analysis of Variance" in Figure 5.14). In general, the mean of probability closeness index decreased continuously from Group 1 through Group 4 and began to increase in Group 5 and continued to increase in Group 6 (see the chart in Figure 5.14). The Student's *t*-test for each pair of group shows that the mean of probability closeness index in Group 1 is significantly larger than Group 4, and the mean of probability closeness index in Group 2 is significantly larger than Group 4 and Group 5 (see "Comparisons for each pair using Student's *t*" in Figure 5.14). The result of Group 1 can be ignored due to the limited observations in Group 1. Most of the pairs in Group 4 and Group 5 involve participants staying in Europe for a while. The valid results from these analyses indicate that the average probability closeness index of pairs in the same region (<500 km) during the last six years was higher than pairs involving participants who stayed or were staying in Europe. The participants in China and the U.S. were more active in the SNS space than participants in Europe during the last six years, which might explain this pattern.




(Each group has a *means diamond*. The line across each diamond represents the group mean. The vertical span of each diamond represents the 95% confidence interval for each group. The horizontal extent of each group along the x-axis (the horizontal size of the diamond) is proportional to the sample size of each group. )

**Analysis of Variance**

| **Source** | **DF** | **Sum of Squares** | **Mean Square** | **F Ratio** | **Probe > F** |
|---|---|---|---|---|---|
| D2_Group | 5 | 0.01440659 | 0.002881 | 2.5354 | 0.0293* |
| Error | 243 | 0.27615217 | 0.001136 | | |
| C. Total | 248 | 0.29055876 | | | |

**Comparisons for each pair using Student's *t* (only pairs significant at the 0.05 level are included)**

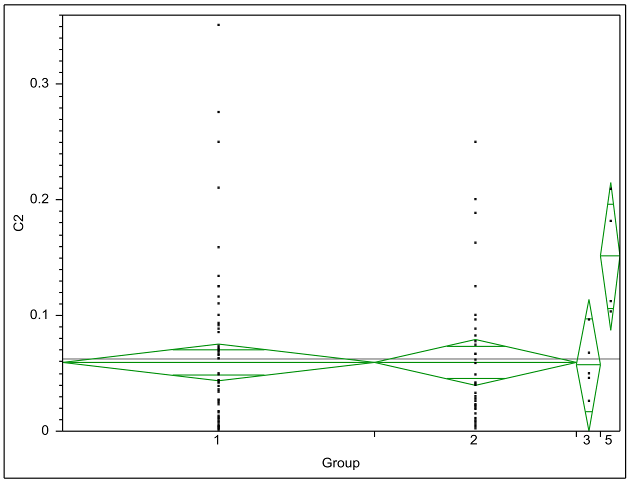
Std Error uses a pooled estimate of error variance

| **Level** | **- Level** | **Difference** | **Std Err Dif** | **Lower CL** | **Upper CL** | **p-Value** |
|---|---|---|---|---|---|---|
| 1 | 4 | 0.0407086 | 0.0204450 | 0.000437 | 0.0809806 | 0.0476* |
| 2 | 4 | 0.0243372 | 0.0086430 | 0.007313 | 0.0413619 | 0.0053* |
| 2 | 5 | 0.0189561 | 0.0074465 | 0.004288 | 0.0336241 | 0.0115* |

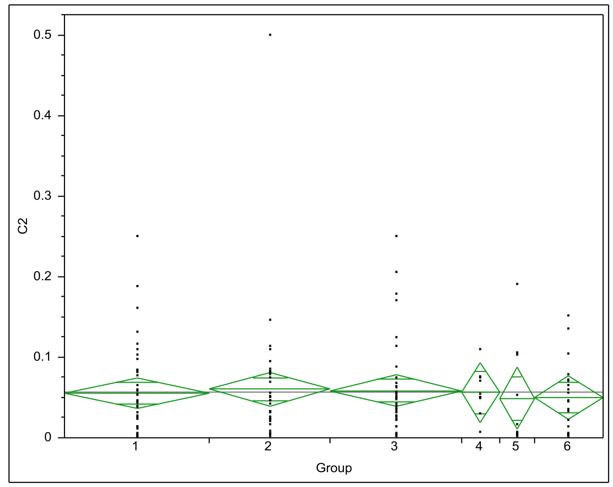
Figure 5.14 ANOVA and Student's t test for means of probability closeness index in different groups of average categorical distance

The combination of *D*2-*C*2 reveals more statistically suggested patterns in the relationship between physical distance and virtual closeness than the combination of *D*1-*C*1, so this study further examined the combination of *D*2-*C*2 in each year. The participants migrated an average of 1.24 times during the six years of study period. Therefore, the average categorical distance in one year can be regarded mainly as the static physical distance between two people.

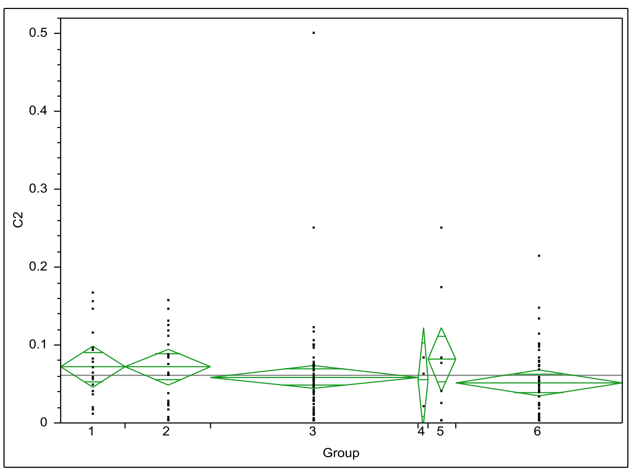
As Table 5.2 shows, fewer than one third of the participants graduated before 2006, thus Figure 5.15a shows that most participants stayed in the same country in 2005. Most of the participants graduated during the period from 2006 to 2007, and some of them then moved to other regions or other countries. In these two years, participants' probability closeness exhibited no difference in different physical distance groups. After 2007, participants had already experienced the transitional period from school to society or to a new school. They had already settled down by 2008, and during this year physical distance began to influence their probability closeness in SNS spaces. From 2008 through 2010, regional probability closeness (Group 1 and Group 2) within the same country were significantly higher than out-of-region communication probability (Group 3). Sometimes regional probability closeness was higher than China-U.S. communication probability (Group 6). These patterns statistically suggest the enhancement effect of physical proximity on SNS closeness between participants living within the same region.



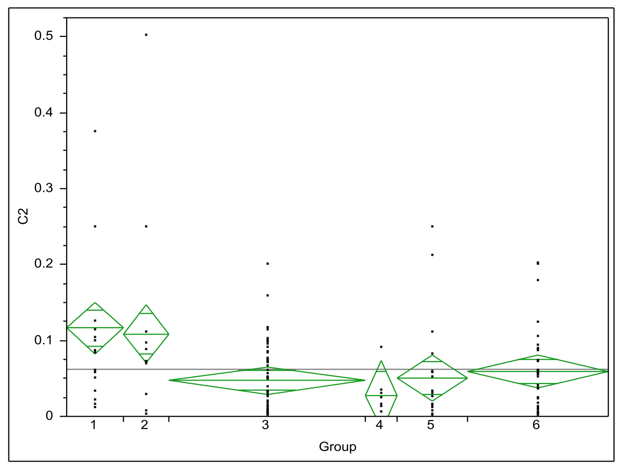

(a) 2005



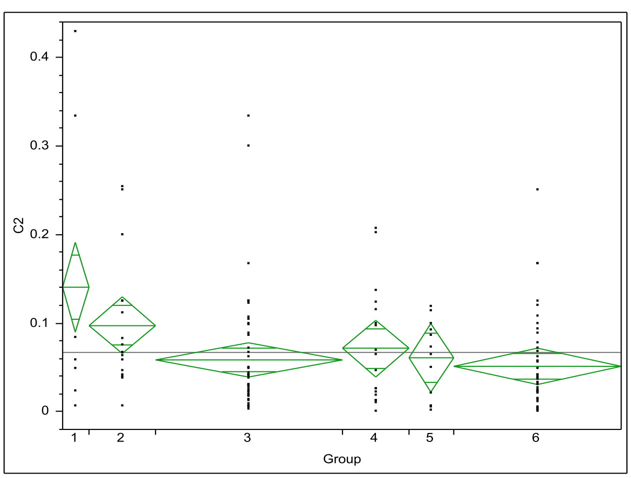

(b) 2006



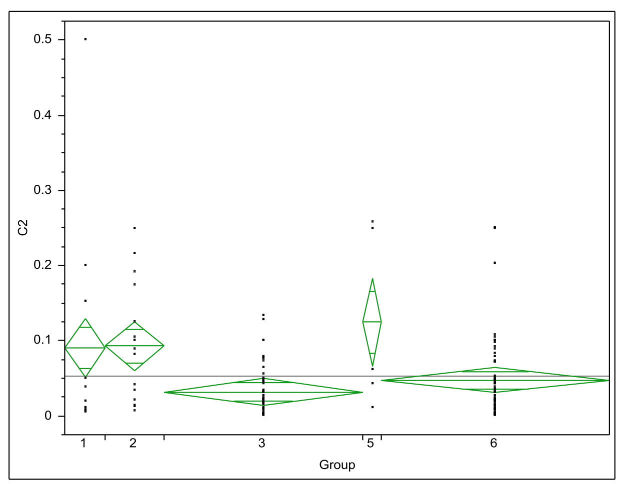

(c) 2007




(d) 2008




(e) 2009




(f) 2010

Figure 5.15 ANOVA for means of probability closeness index in different categorical distance groups in each year

This study analyzed the physical proximity and virtual closeness variables with classical statistical analysis. The results indicate that the physical proximity measurement based on categorical distances performs better than it based on geographical distances. Moreover, the closeness measurement based on visit probability considers interpersonal closeness relative to other friends, which the closeness measurement based on communication counts does not address. The probability closeness index thereby is more helpful than the count closeness index for this case study. Over the six years, there was no general decline in virtual closeness over physical distance among the participants, but a regional enhancement effect is found. The investigation of patterns in each year reveals the evolution of participants' relationships in their SNS space, and how the regional enhancement effect emerged over time.

### *5.4.3 Patterns of dynamic process in virtual closeness changes with physical proximity changes*

The dynamic process discovered in the last section is still based on aggregate patterns. In classical statistical environments, there is no straightforward way to trace each pair of friends and to reveal how the discovered evolving patterns formed by each pair of friends. This section focuses on the SNS closeness change for a pair of participants as their physical proximity changed over time. For example, after graduation and staying apart for a period, did two close friends communicate less in SNS? Or will two classmates who have never talked in their SNS space start to communicate and become close in their SNS space after relocating to the same place? What are the percentages of different patterns occurring among the participants? This section applied the 3D cluster approach discussed in Section 5.1.2 to answer the above.

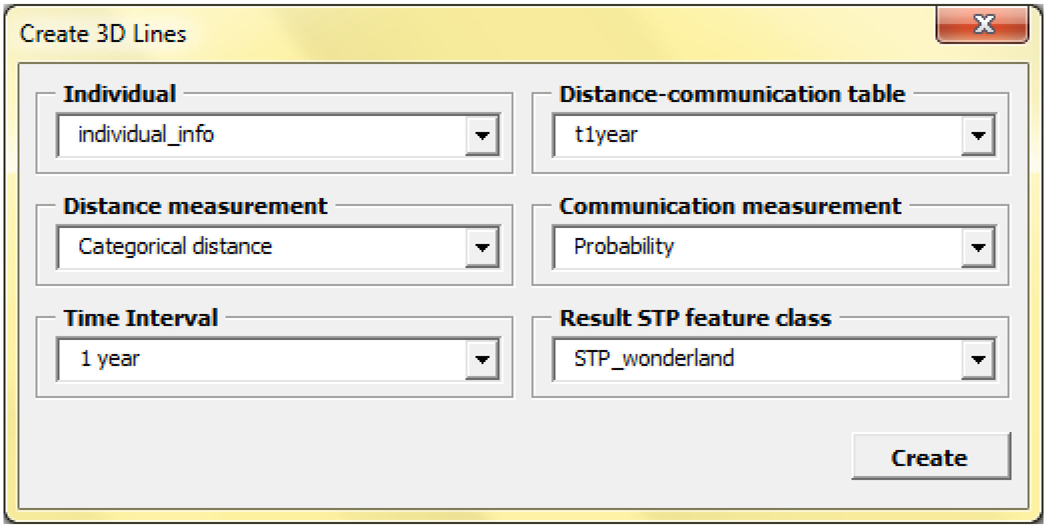



Figure 5.16 The tool to create 3D lines

This 3D line generator was also developed in ArcScene 9.3 (Figure 5.16). It takes an individual information table and a distance-communication table as input. The distance-communication table is created by the variable generator shown in Figure 5.8. Users also have to set the physical distance measurement, the virtual closeness measurement, and the time interval to match the selected distance-communication table. The 3D lines will be generated in the "Result STP feature class".

The combination of *D*2-*C*2 indicated its effectiveness for this study's dataset, so average categorical distance and virtual closeness index based on visit probability were applied to two axes in the 3D coordinate system. The distribution of *C*2 has a long tail toward the large value, which is an exponential distribution (verified by the distribution fit examination) (Figure 5.12). For a better representation, Log(*C*2) was used for the closeness axis, and value 0.0001 was used to substitute value 0 of *C*2. The temporal axis resolution depends on the time interval of measuring SNS closeness. This study used a one-year interval to capture the general trend during the six years period.  As a result, 249 3D lines were generated for the 249 pairs of connected participants. The relationship between any two of the three variables can be examined by rotating the observation angle (Figure 5.17).

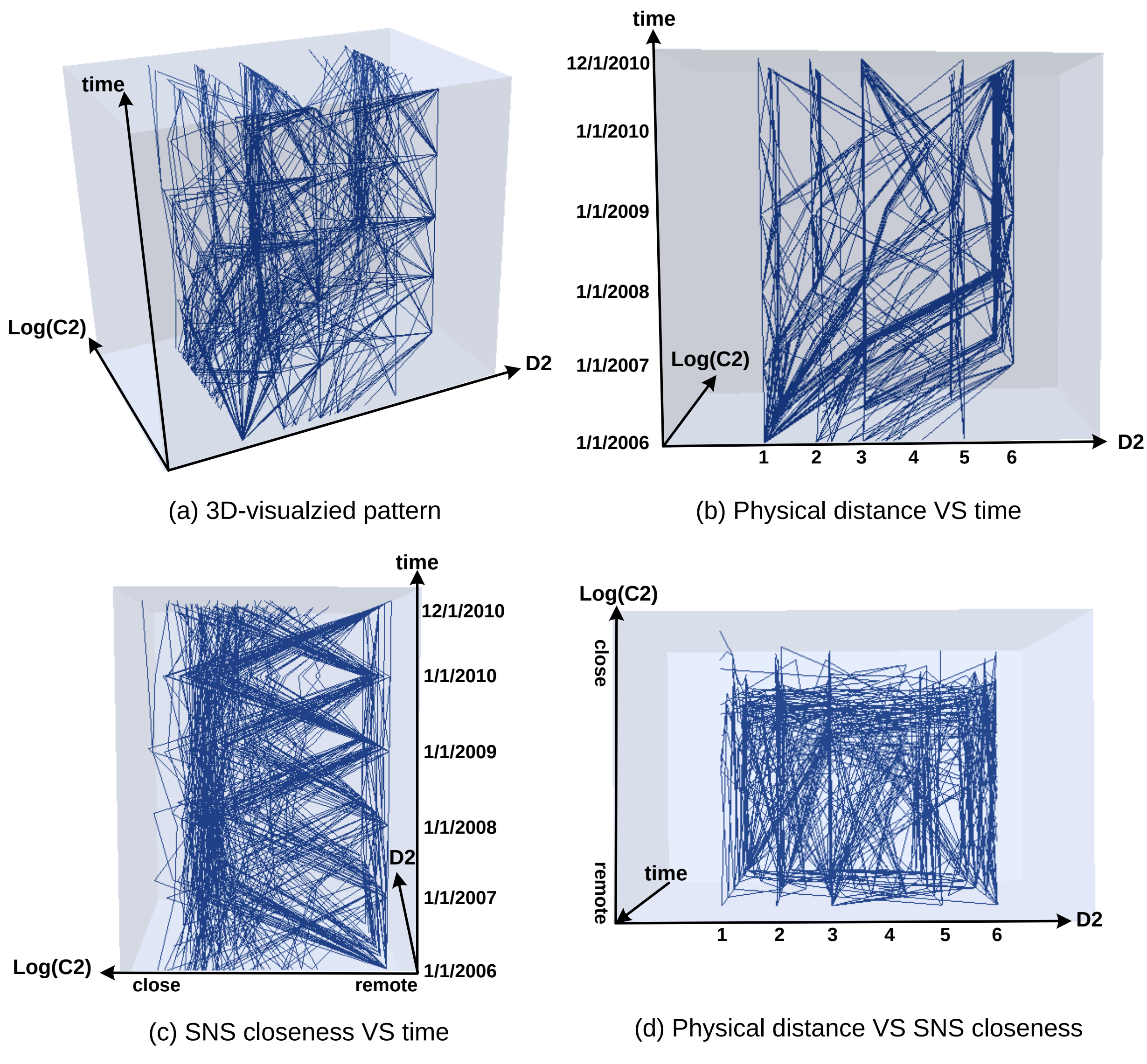



Figure 5.17 The 3D-visualized relationship among physical distance, SNS closeness, and time for pairs of participants

According to Table 5.1, this study divides 249 pairs of participants into two groups by their initial status of SNS closeness. The *initially far group* and the *initially close group* were identified by probability closeness index in 2005. Of these, 133 pairs of participants, who did not communicate in the SNS space in 2005, are marked with initially far status; the other 116 pairs are considered to be initially close in the SNS space. The cluster analysis tool shown in Figure 4.20 allows exploration of patterns in a user-customized way. Users are able to choose different clustering methods (e.g., hierarchical or k-medoids clustering), set different number of clusters, compare cluster results, and acquire useful information from different settings. This study used the *k*-medoids clustering method and respectively conducted cluster analysis for the initially far and close groups. 34 out of 37 participants were living in Nanjing City at the beginning of the study period, so right after the beginning most of the physical distance changes are in "no change" or "increase" situation. In this case, for each initial closeness status, there might be mainly four typical patterns (see Table 5.1). As a demonstration, in the following experiments, the case study set four clusters for each group to discover patterns. Of course, "physical distance decrease" situations happened for some of the participants in the middle of the six years, and some real situations involve different situations mixed. The number of clusters can be increased if observation with finer resolution is in need by users.

Using the function for creating generalized space-time paths in the cluster analysis tool, Figure 5.18 displays the four groups among the pairs of participants with initially far status. Groups 1 and 2 both clearly show Pattern 6. The physical distance between pairs of participants in Group 1 increased on average from 2005 to 2007, and finally stabilized at cross-country distances after 2008 (Figure 5.18b). Their SNS closeness accelerated suddenly during 2006 and then remained at the same level of closeness in the following years (Figure 5.18a). Participants in

Group 1 did not talk on the social networking websites before graduation, but they communicated intensively during the year after they relocated to different countries. It can be assumed that they were close friends and had opportunity for frequent face-to-face communication before graduation. Subsequently, when they were in different countries they had to communicate via social networking websites. Thus, their closeness in SNS space dramatically rose right after graduation. The average physical distance in Group 2 also increased, but limited to the same country. Compared with Group 1, Group 2's average SNS closeness increased steadily over the six years. These participants were probably lukewarm friends before graduation and communicated in the SNS space only occasionally, or perhaps they had some face-to-face meeting opportunities or opportunities for phone communications in the same country, which might mitigate their dependency on SNS. Group 4 had physical distance changes similar to those of Group 1, but the SNS closeness climbs slowly during the six years. These participants may not have been close friends before graduation, and they did not become closer after graduation. Their activity more resembles Pattern 5. Group 3 demonstrated the characteristics of Pattern 6 during the first three years and of Pattern 8 in the following three years. They relocated to other cities and kept in contact in SNS space during the following two years after graduation; they then became gradually more distant, which is a common trait among alumni.

Figure 5.19 displays the four groups among the pairs of participants with initially close status. Group 5 and Group 7 both have close relationships in SNS space before graduation, and the average physical distances after graduation between participants in Groups 5 and 7 were all limited to the same country. Over time, Group 5 relationships in the SNS space still remained close (Pattern 11), but participants in Group 7 gradually grew remote and finally stopped contact in the SNS space (Pattern 12). Participants in Group 6 were as close as those in Group 5 in SNS space at the beginning. After they moved apart to different countries, their SNS closeness slipped a little (more like Pattern 12). Group 8, with a small percentage of pairs of participants, exhibited a fluctuating pattern during the six years. Participants in Group 8 were mostly non-active users of the social networking services, although they occasionally ventured into SNS space, which led to the unique pattern in Group 8 (refer to the noise participants in Chapter 4).

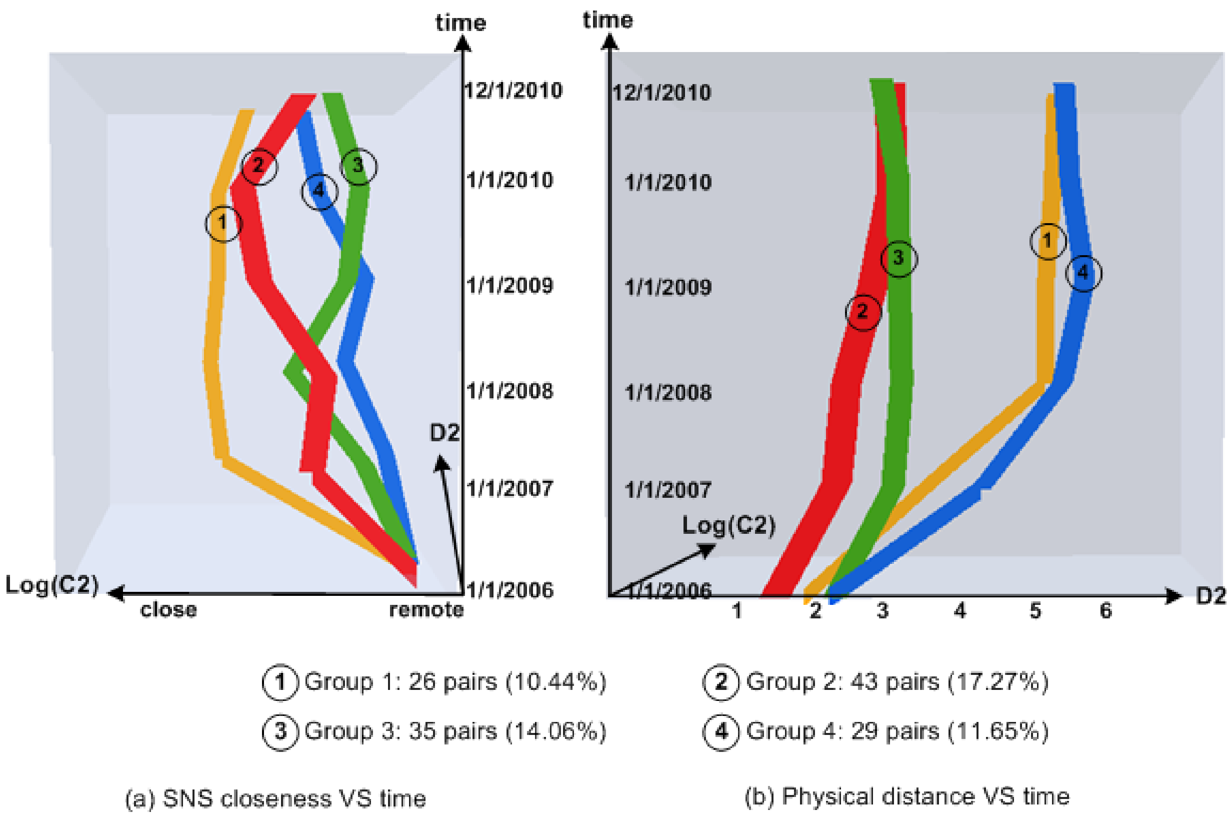



Figure 5.18 The four patterns of SNS closeness change with physical distance change over time for pairs of participants with initially far status

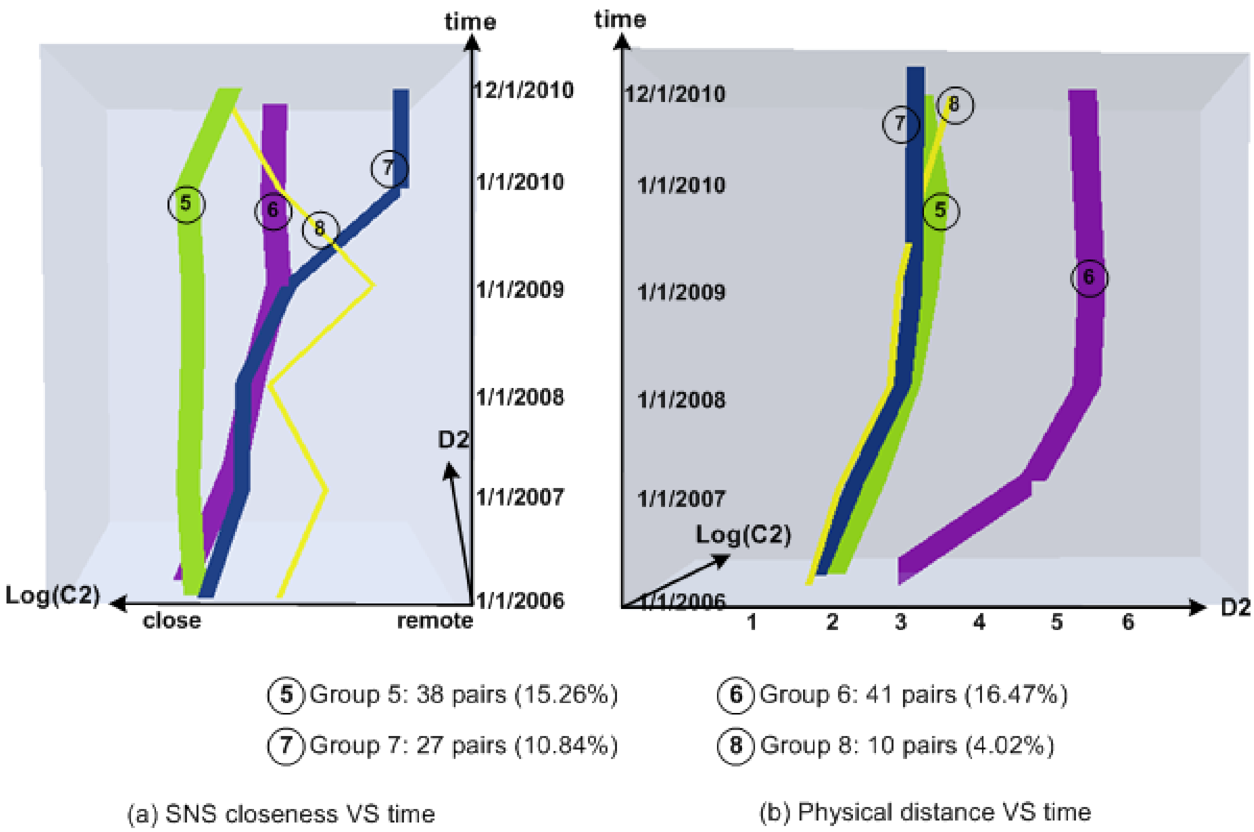



Figure 5.19 The four patterns of SNS closeness change with physical distance change over time for pairs of participants with initially close status

As Table 5.3 summarizes, after most of participants moved away from the same place, there was no unified or general pattern in their closeness change on the social networking websites. In other words, their migration affected their SNS closeness in various ways. Out of all participants, most of the close friends who already took advantage of SNS before graduation maintained frequent communications in the SNS space after graduation (Groups 5 and 6), while a small portion of friends gradually became distant in the SNS space (Group 7). Those close friends who did not use SNS before graduation started communicating in SNS space right after graduation (Group 1). Of course, some participants who were distant in SNS before graduation did not develop significantly more connections in SNS after graduation (Group 4); some of them communicated for a period after graduation and then gradually became remote (Group 3).

Table 5.3 Percentages of different patterns of SNS closeness change with physical distance change over time

| Pattern | Initial status of SNS closeness | Physical distance change | SNS closeness change | Groups | Percentage |
|---|---|---|---|---|---|
| Pattern 5 | Remote | Increase | No change | Group 4 | 11.64% |
| Pattern 6 | Remote | Increase | Become close | Group 1, Group 2 | 27.71% |
| Pattern 11 | Close | Increase | No change | Group 5, Group 6 | 31.73% |
| Pattern 12 | Close | Increase | Become remote | Group 7 | 10.84% |
| Non-typical patterns | Remote | Increase | Become close, then turn remote | Group 3 | 14.06% |
| | Close | Increase | Fluctuate | Group 8 | 4.02% |

### *5.4.4 Virtual closeness changes with physical proximity changes for a person with others*

The last section discussed relationships between individual participants in pairs, and treats each relationship independently. Actually, the 249 relationships are derived from 37 participants. Is there an association between different patterns and individuals? For instance, do some participants always abandon their close relationships in SNS once they are physically separated? Or, do some participants always maintain or strengthen their relationships with alumni via SNS after graduation despite their physical locations?

To answer these questions, this study designed Figure 5.20. Each color of a horizontal bar stands for a pattern. For a participant, the length of a color represents the percentage of the pattern among all patterns emerged in his/her relationships with others. In terms of maintaining a relationship, Pattern 5 and Pattern 12 can be considered to be passive attitudes, Pattern 6 and Pattern 11 as positive attitudes, non-typical patterns as unclear attitudes. As a result, all participants show at least two types of attitudes. In other words, none of the participants in this study used simple ways to handle their relationships with alumni. Yet, some participants still had preferences between passive and positive attitudes. For example, Linn displayed an attitude for maintaining her connections with alumni that was much more positive than passive (the total length of her grey and green bars is longer than the length of her blue bar). In contrast, Helen had the opposite preference (the total length of her blue and purple bars is longer than the length of her grey bar). This study defined people with more positive attitudes regarding the maintenance of connections as *positive actors*, people with more passive attitudes as *passive actors*, and those in the middle as *neutral actors*. In the results, 78% of the participants were positive actors, 11% were passive actors, and 11% were neutral actors. Positive actors tended to communicate with friends in SNS spaces, whether they were in the same city or in different countries. Therefore, a high percentage of positive actors in the study group can explain to some extent why no general relationship was found between SNS closeness and physical proximity across the entire world from the participants (Section 5.4.2).

This study also developed a tool in ArcScene 9.3 to produce a relative physical distance chart and a virtual closeness rank chart. As Figure 5.21 shows, after selecting physical migration table, individual information table, virtual communication table, and the feature class of physical space-time paths, users can also set time interval of ranking virtual closeness and the ego person.

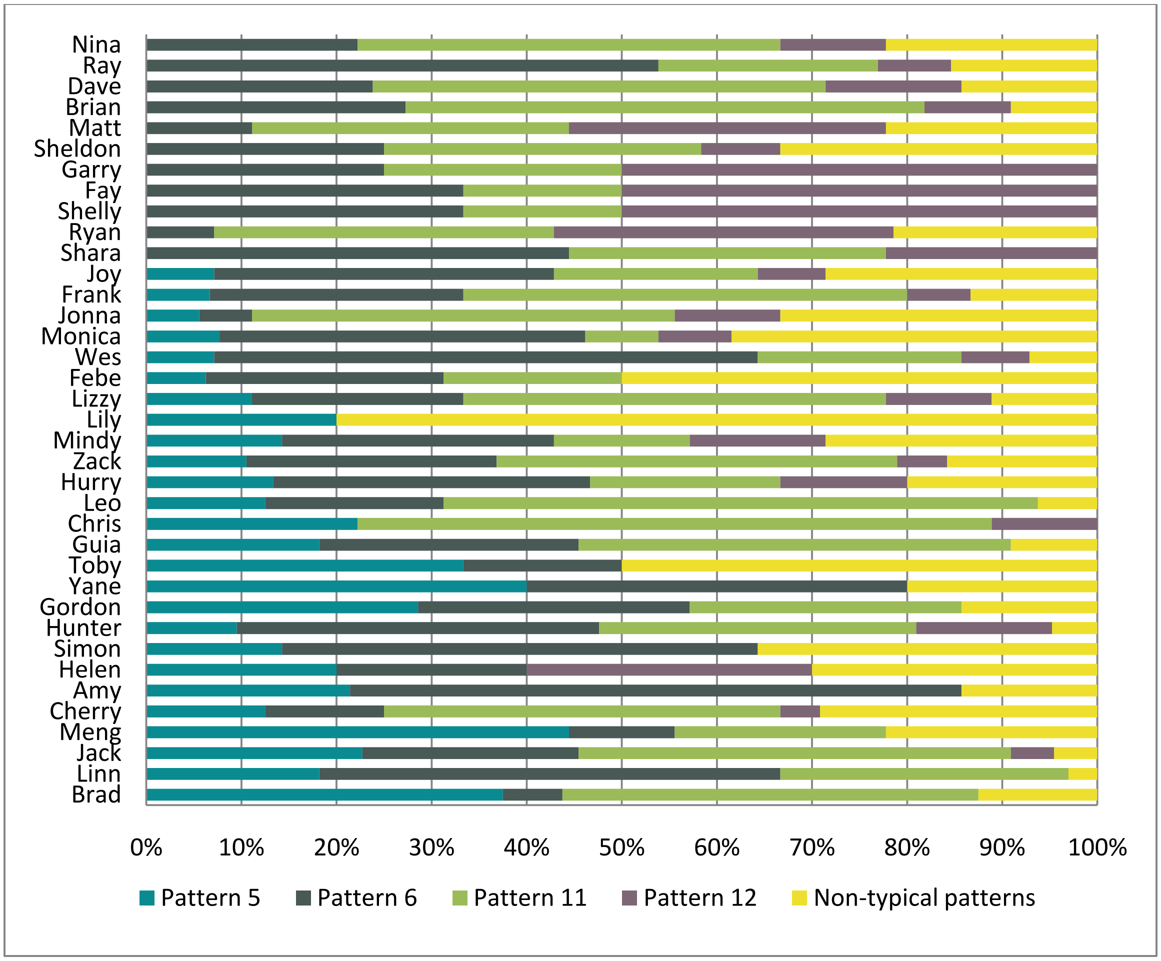



Figure 5.20 The percentage of each pattern among all relationships of a participant

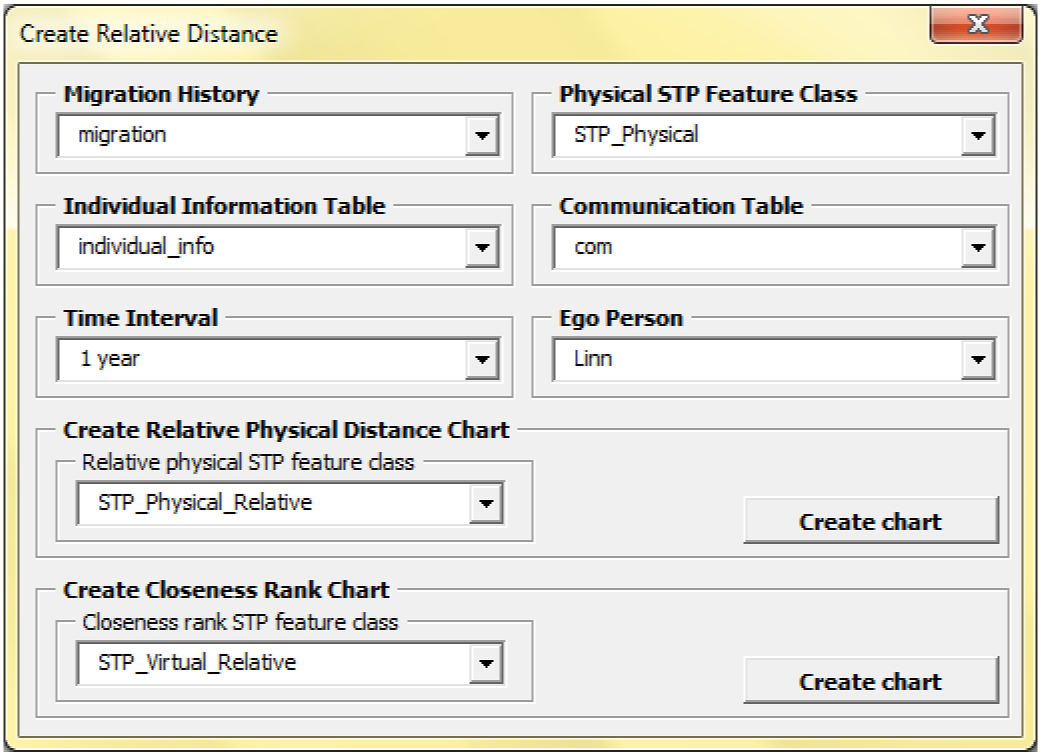



Figure 5.21 The tool to compare relative distance between a person and his/her friends in both physical and virtual spaces

Figure 5.22a demonstrates the relative physical distance chart based on Linn. The horizontal axis refers to categorical physical distance ranging from 1 to 6, while the vertical axis represents time. The left red vertical line stands for the ego person. To the right of the ego line, each grey line represents a friend. The overall pattern of all her friends' relative distances shows that Linn was living in a different country from most of her friends after the second half of 2006. Linn's physical space-time path shows that she moved to the U.S. from China in August 2006. Additionally, the green line is a highlighted friend A. A closeness rank chart, on the other hand, traces the closeness rank of an ego's friends over time. Virtual closeness is measured based on visit probability in this chart; the horizontal axis refers to closeness rank in an ascending order from left to right (Figure 5.22b). Each brown line represents a friend, and the green line is the same friend highlighted in the relative physical distance chart.

These two charts together portray a comprehensive story about the ego person in terms of his/her relationships with friends in both physical and virtual spaces. During the year Linn moved to another country, her friends in SNS space dramatically increased (brown lines move from the unconnected end to the connected queue). Linn and her friend A began communication by SNS after Linn moved to the same country with this friend. After that, their SNS closeness rose steadily, and till the most recent year of the study period this friend had become one of Linn's best friends in SNS space. Turning to friend B, who did not leave Nanjing city, Figure 5.22c and d describe a different relationship change. During the year of moving to the U.S., Linn and friend B started to keep in touch via SNS. After a while, their communication gradually declined, and in the most recent year, they were completely distant in SNS space. These patterns might indicate the effect of physical proximity on social ties. Physical proximity offers people more face-to-face opportunities, similar social and cultural context, the same identity of co-location, better institutional maintenance of phone communication, and similar time zone facilitating synchronous communication. These factors might influence friendship, and social networking websites may catch such impact.

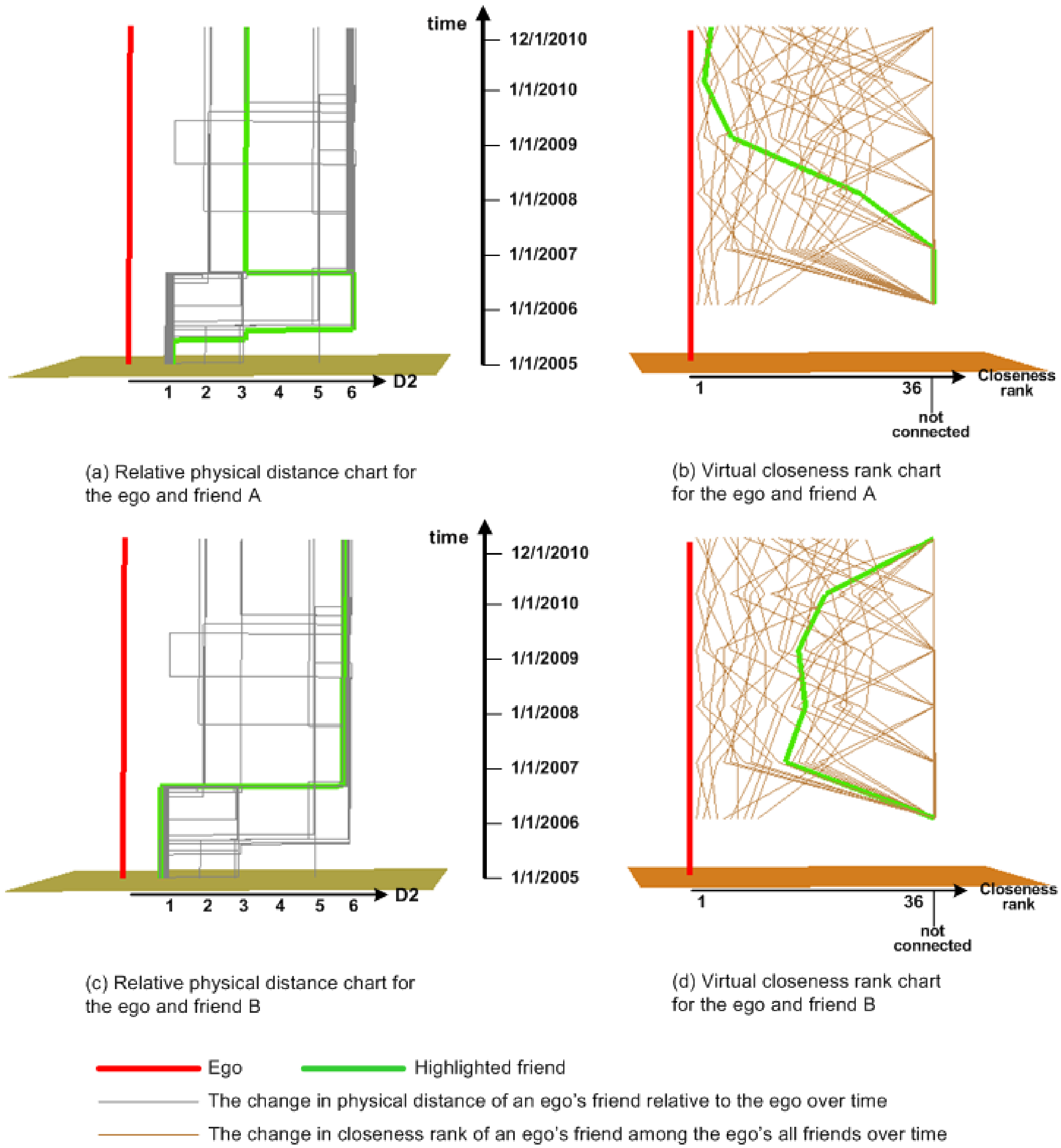



Figure 5.22 A participant's relative physical distance chart and closeness rank chart

In summary, Section 5.4.1–5.4.3 examined the relationships between physical proximity and virtual closeness. It first applied classical statistical tools to examine the aggregate relationship between physical proximity and virtual closeness. Then it developed the spatial-temporal analysis tools to trace each interpersonal relationship, and to visualize and explore the dynamic interactions between physical proximity change and virtual closeness change. These two analysis environments reveal different patterns, complementing one another with their own applications and advantages.

### *5.4.5 Measurements of temporal proximity and communication time-lag*

People generally communicate more efficiently during synchronous communications (Storper and Venables, 2004; Tillema *et al*., 2010). Therefore, instantaneity of communication might affect interpersonal relationships. Time zone difference exists as another form of geographical distance, and such time differences may cause inconvenience for synchronous telecommunication between people in different time zones. Social networking services provide platforms for asynchronous communications, yet response time is still affected by time differences. The following two sections' objective is to investigate the relationship between temporal proximity and communication time-lag.

This study defines temporal distance between two persons as the time difference between the two persons' local time (taking into consideration of daylight saving time). Person A's communication time-lag with person B refers to the absolute time difference between the time person B posted on a website and the time of person A's first response. A post and all of its comments are identified by a unique conversation ID (see Table 4.4), so the communication time-lag of each comment between two persons is measurable in this study. Because Kaixin Website has more timely interaction than Lily Blog, only communication records on Kaixin Website were used for this examination. Excluding the comments on a person's own post, in total there were 1,251 interpersonal comments among the participants on Kaixin Website since it was launched in 2008. The variable generator shown in Figure 5.8 created a record for each comment. Each record included post time zone, post time in local time, response time zone, response time in local time, and communication time-lag in hours. Most communication time-lags are within 24 hours. To avoid possible outliers, this study only includes records with communication time-lag less than 24 hours. Participants in Europe were not active, having been only associated with 72 records. Their records were also excluded. As a result, there were 874 records associated with participants in the U.S. and China left in the study.

### *5.4.6 Temporal proximity and communication time-lag*

This study defined four groups of temporal proximity (Table 5.4), and used ANOVA to compare average communication time-lag among the four groups in four post time periods of a day: 0 AM–6 AM, 6 AM–12 PM, 12 PM–6 PM, and 6 PM–12 AM. Four ANOVA tests were statistically significant at the 0.05 level, which indicated an association between temporal distance and communication time-lag.

During 0 AM–6 AM local time, as Figure 5.23a exhibits, posts from the U.S. (Group 1 and Group 2) significantly exceeded posts from China (Group 3 and Group 4). Because most participants in the U.S. were graduate students while most participants in China were full-time employees, more online activities in the early morning might be the result of different life styles between students and working people. Group 2’s mean of response time was statistically smaller than Group 1’s mean (significant at the 0.05 level in the Student *t*-test). This shows more timely response from China than from the U.S. to the posts from participants in the U.S. during the early morning, because participants in China are more likely to be online and respond to posts in the afternoon.

For posts between 6 AM–12 PM local time, participants in China had shorter average first response time to posts from China (Group 3) than to posts from the U.S. (Group 2) (significant at the 0.05 level in the Student *t*-test). When participants in the U.S. posted during the morning, participants in China were going to sleep early for the next day's work, so many of them responded such posts the next day (Figure 5.23b).

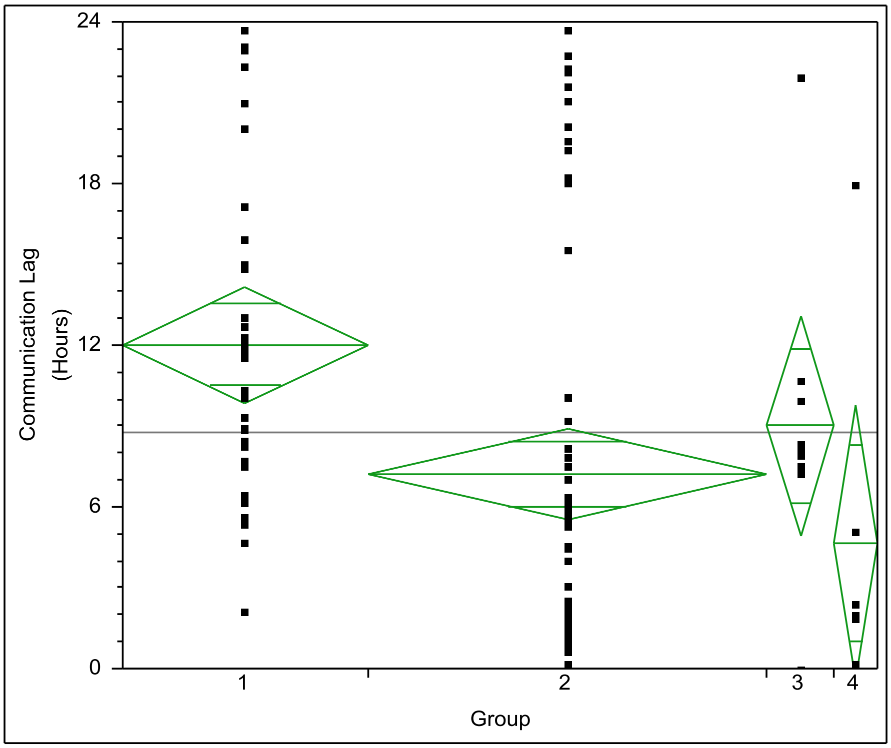
For posts between 12 PM–6 PM local time, participants in China still had shorter average first response time to posts from China (Group 3) than to posts from the U.S. (Group 2) (significant at the 0.05 level in the Student *t*-test). When participants in the U.S. posted during their afternoon, participants in China were already sleep, so the fastest response appeared after they got up the next day (Figure 5.23c). The same holds true for participants in China who posted online during the afternoon local time, average response speed from China (Group 3) was faster than from the U.S. (Group 4) (significant at the 0.05 level in the Student *t*-test).

The most active period for participants in their SNS spaces was 6 PM–12 AM. Comment records during this period accounted for almost one third of all comment records. People within nearby time zones only had two opportunities to respond posts appearing at night, one before sleep and the other one after getting up on the next day. People on the opposite side of the world, however, had all day to respond to posts appearing during the morning local time. As a result, the average communication time-lag between participants in the same country (Group 1 and Group 3) for posts in the evening was statistically longer than between participants with the maximum time difference between the U.S. and China (Group 2 and Group 4) (Figure 5.23d).

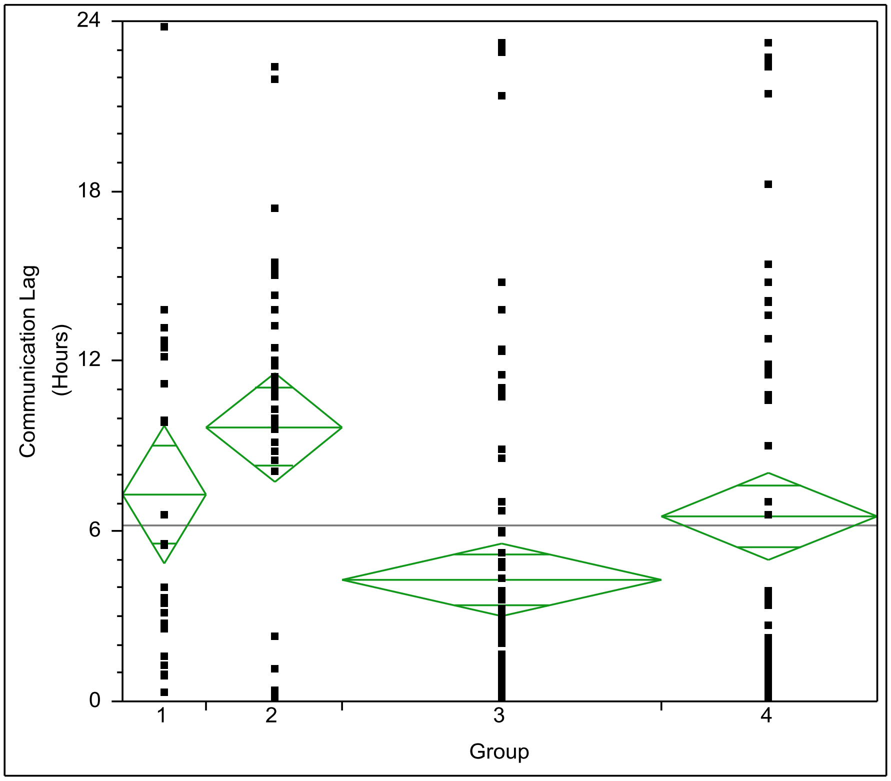
Overall, for posts during evening and early morning hours (6 PM–6 AM the next day), participants on the other side of the world had faster average response speeds. For posts during the day time (6 AM–6 PM), participants in the same country had faster average response speeds.

Table 5.4 Four groups of temporal proximity among selected participants

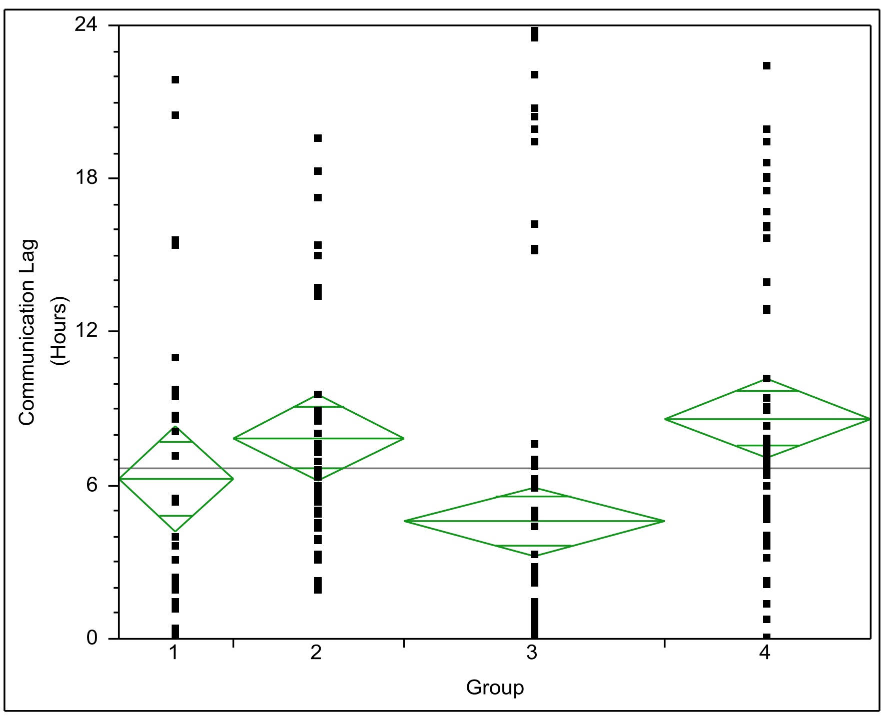
| Group | Post location | Response location |
|---|---|---|
| Group 1 | the U.S. | the U.S. |
| Group 2 | the U.S. | China |
| Group 3 | China | China |
| Group 4 | China | the U.S. |



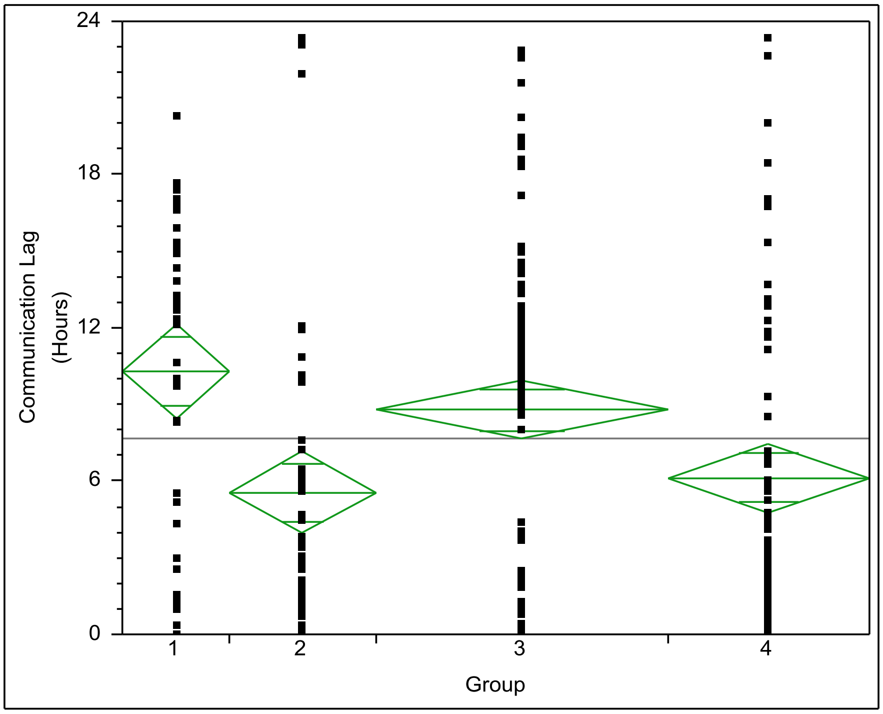

(a) For posts during 0 AM–6 AM local time




(b) For posts during 6 AM–12 PM local time




(c) For posts during 12 PM–6 PM local time



(d) For posts during 6 PM–12 AM local time

Figure 5.23 ANOVA result of average communication time-lag by temporal distance for posts in different time periods

### *5.4.7 Temporal proximity and virtual interaction opportunities*

Virtual space-time prisms presented in Chapter 4 can help explain the patterns discovered from the last section at the individual level. For instance, according to Jack's virtual probabilistic space-time prisms (Figure 4.28a), he might publish new posts in the four different time periods on a Monday (U.S. Eastern Standard Time). If he posted sometime at 0 AM–2 AM, Brad—living in the same time zone—would not respond until at least 12 hours later when he can get on the Internet in the afternoon of next day (Figure 4.28b). However, because Zack lived in China, he had opportunities to respond the post of Jack within 6 hours (Figure 4.28c). If Jack posted during the time from 12 PM to 3PM, it was possible for Brad to respond right away, yet Zack had to wait till the next morning. Virtual space-time prisms offer an alternative approach to facilitating understanding individual behavior in virtual space.

### *5.4.8 A spatio-temporal exploratory environment*

The spatial-temporal exploratory tools presented in Chapters 4 and 5 complement one another, and together they form a comprehensive analysis environment for exploring human interactions in virtual space and their relationships with physical spatial-temporal proximity. The comprehensive analysis environment is implemented in ArcScene 9.3. Within the space-time GIS, users can observe interpersonal relationships in both physical and virtual spaces at the same time (Figure 5.24). Users also are able to choose which exploratory analysis to be displayed in the environment, and to zoom into the analysis of interest. Figure 5.24 turned on all spatial-temporal exploratory views with a focus on the relationship between Linn (red line) and Guia (green line). Their physical space-time paths show their migration pattern based on the world map; they both moved from China to the U.S. The relative physical distance chart more intuitively reveals Guia's physical distance change relative to Linn. At the same time, their social space-time paths illustrate the change in their positions within the entire social network during the six years. They both moved toward to the center of the social network and became closer during the study period. The virtual closeness rank chart relative to Linn indicates their closeness change in the SNS space. The 3D cluster analysis identifies their relationship in Group 2 with Pattern 6 (see Figure 5.18), which indicates they became closer in the SNS space with physical distance increase after graduation. The bottom-right of Figure 5.18 displays their virtual space-time prisms on a weekday. Their online time windows are close to each other and have some overlapping. Such activity patterns offer them opportunities of instant communication, which may strengthen their friendship. As a result, we may conclude that their similar migration patterns and physical proximity in recent years are closely related to their SNS closeness change.

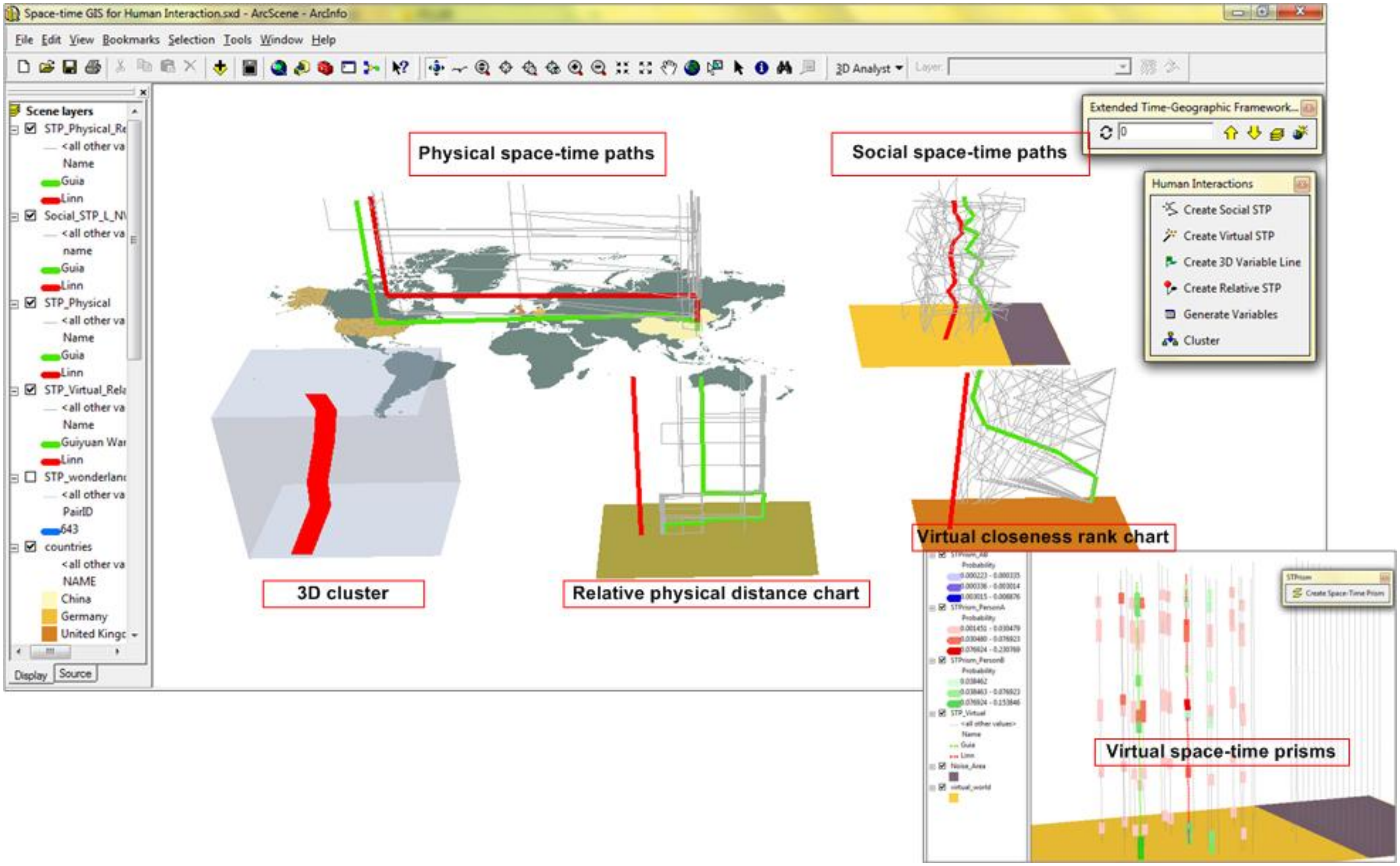



Figure 5.24 A space-time GIS for exploring human interactions in both physical and virtual spaces

## 5.5 Summary

This chapter presents a spatio-temporal environment to explore the impact of physical spatial-temporal proximity on human interactions in virtual space. The spatio-temporal environment complemented classical statistical tools with its better capacity in visualization and user-interactivity, as well as specialized analysis functions for spatial-temporal data. It is particularly capable of tracing the dynamic relationships between physical proximity change and virtual closeness change for a pair of individuals. It also can identify different patterns among dynamic relationships in a group of people. In addition, users can compare two individuals' virtual activity time during the course of a day, which associates with the instantaneity of their virtual communication.

To demonstrate how the exploratory environment presented here can work with classical statistical environments, this study used the dataset obtained from the author's 37 classmates at Nanjing University. The survey showed that social networking websites were important to the participants maintaining friendships after graduation. The results from classical statistical tools indicated that during the period from 2005 to 2010 participants had a higher probability of communicating with participants living in the same region (<500 km) on their social networking websites than with participants living further away. The 3D cluster analysis in the space-time GIS then suggested four different relationships between physical proximity changes and virtual closeness changes over time. The results showed diversity among the ways participants maintained their relationships with alumni. They also revealed that around three quarters of the participants hold relatively positive attitudes toward maintaining their connections with alumni on social networking websites. With respect to the effect of temporal proximity on communication time-lag in SNS spaces, if participants posted during evening and early morning hours, their friends on the other side of the earth typically provided more speedy responses than did their friends in the same country. If they posted during the day time, friends in the same country responded faster on the whole. In a nutshell, spatial-temporal distance does not constrain human interactions as strictly as before the ICT age, but they still affect human interactions in virtual space in various ways.

Within the large body of literature that discusses the complex impacts of geography on social connections in the ICT age, there are few studies examining the dynamic process of the impacts in a spatial-temporal exploratory environment. This study demonstrates the effectiveness of a space-time GIS for exploring such a complex process and facilitating the understanding of human interactions in the ICT age from a spatio-temporal perspective.

# CHAPTER 6 CONCLUSION

## 6.1 Summary of the Study

Information and communication technologies (ICT) are changing human daily activities and interactions. Some researchers have argued that such changes could influence travel patterns, individual accessibility, social network, and many other aspects of society (Mokhtarian, 2003; Schwanen *et al.*, 2008; Yu and Shaw, 2008). As part of a broader effort of studying human activities and interactions in the ICT age, this dissertation seeks to develop analytical frameworks and exploratory tools based on a spatio-temporal perspective to better understand human interactions in physical and virtual spaces. In particular, this study addresses three research questions.

First, this study extends the time-geographic framework to assess the impacts of phone usage on potential face-to-face (F2F) meeting opportunities, as well as dynamic changes in potential F2F meeting opportunities over time. A number of studies have discussed ICT impacts on individual activities in the physical world (Mokhtarian, 2003; Schwanen and Kwan, 2008). However, these studies did not focus on presenting an analytical framework that can articulate the mechanisms by which ICT affect activity constraints at the individual level, nor did they assess to what extent ICT potentially impact individual physical activities. Due to the variability in situations of ICT influencing individual activities, this study chooses a typical scenario to analytically depict the process of virtual communication altering physical interaction opportunities in space and time.

Secondly, this study extends the time-geographic framework to conceptualize and represent individual trajectories in an online social network space and to explore potential interaction opportunities among people in a virtual space. Some studies visualized the paths that users take through websites and the spatial scopes of an individual's virtual communication in a three-dimensional space (Cugini and Scholtz, 1999; Adams, 2000; Kwan, 2000). Some researchers believed that the emergence of virtual space brought in a new dimension to geography (Batty, 1997; Giese, 1998; Crang *et al.*, 1999). There is need for a framework that systematically conceptualizes, represents, and analyzes virtual activities and interactions. This study is a starting point to develop such a framework by extending the time-geographic framework.

Thirdly, this study presents a spatio-temporal environment to facilitate exploration of the relationships between changes in physical proximity and changes in social closeness in a virtual space. With the claim that physical distance is annihilated by ICT, a large body of literature discussed the complex effects of geography on social connections in the ICT age (Harvey, 1989; Mok *et al*. 2009). Few studies scrutinized changes in interpersonal relationship in virtual space when physical proximity also changes. This study develops a spatio-temporal exploratory environment for investigation and understanding of such a dynamic process.

This study advances time geography in its capability of exploring processes of ICT access that affects physical activity opportunities. Generally, the time-geographic framework treats individual activities as either fixed activities or flexible activities according to their degree of flexibility in space and time. To reveal the impact of ICT on activity opportunities—particularly when activity schedules change over time—this study reclassifies fixed activities as *routine fixed activities* and *non-routine fixed activities*, and refers to planned routine and non-routine fixed activities as *planned activities*. Based on these basic concepts, this study presents *in plan* and *out of plan* conditions and *keep plan* and *update plan* actions for an individual at any moment to reflect dynamic activity scheduling during a day. Planned activities and meeting opportunities could be updated during a phone communication. This study thus points out that a *complete phone communication* between two people is a key step for arranging a F2F meeting. Given an individual's current status at a specific time point, the proposed framework computes potential F2F meeting opportunity sets before and after the potential earliest complete phone communication. It then combines these two meeting opportunity sets as a complete set of all potential F2F meeting opportunities. As phone communication affecting potential F2F meeting opportunities, many situations of ICT impacting individual activities involve processes. Exploring a process usually includes examining current status at a particular time moment, responding to the current status, and reasoning future conditions according to current status and responses. This study offers an example of how to explore a process under an extended time-geographic framework. As discussed in Section 2.3, classical time-geographic frameworks belong to constraints-based approaches. They do not incorporate decision-making rules, individual preferences, or simulations. This study seeks to extend the time-geographic framework by introducing reactions to a current status. It demonstrates the way of extending a time-geographic framework to explore a process, which is important to explore individual activities and interactions under the influence of ICT.

Another contribution of this study to time geography is its extension of some concepts from a physical space to a virtual space. Based on an online social network space, this study defines a *virtual space*, a *virtual place*, a *virtual movement*, and *constraints on virtual activities*. With these basic concepts, this study defines a *virtual space-time path* to depict an individual's trajectory in a virtual space. It also defines *virtual space-time prisms* to identify the space-time possibilities of an individual's virtual activities and interactions conditioned by the proposed constraints. It further defines *virtual probabilistic space-time prisms* to identify the space-time probabilities of an individual's virtual activities and interactions. By representing these concepts in a virtual space based on geographical maps and social networking graph, this study suggests a multi-representation for the extended time-geographic framework. Moreover, a *social space-time path* approximates an individual's relative positions in a dynamic social network. It presents another individual trajectory in a virtual social space. With these revisited as well as new concepts, this extended time-geographic framework can facilitate our exploration and understanding of individuals' activity and interaction patterns under various constraints in a virtual space.

This study also contributes to the development of a space-time GIS. The space-time GIS adopts a three-dimensional environment to include a two-dimensional space and a third dimension of time as the work of Yu and Shaw (2008). This study follows the Yu and Shaw's approach (2008) to derive the potential F2F meeting opportunities between two persons based on a transportation network. The main difference is that the tool in this study considers individuals' phone access situations and their influence on potential F2F meeting opportunities. In addition, this tool can generate potential F2F meeting opportunities at any chosen time moment so that users are able to check the changes of F2F meeting opportunities over time. This study develops several spatio-temporal exploratory functions in the space-time GIS to handle virtual activities and interactions. With a group of people's online communication records and physical movement records over a period of time, this space-time GIS is capable of creating their trajectories in a virtual space, including social space-time paths and virtual space-time paths based on either their geographical locations or their relative locations within a social network. A cluster analysis tool is developed in this space-time GIS to identify groups of people with various physical, virtual, and social relationships. Given the input of social space-time paths, it can explore subgroups with similar trajectories in a social network and create a generalized space-time path to represent each subgroup's aggregate pattern. Based upon online communication data, the space-time prism generator can analyze and create activity probabilities at accessible virtual places during a particular day of the week. It also creates synchronous communication probabilities at commonly accessible virtual places for two people during a particular day of the week. In order to compare the changes in physical proximity and changes in virtual closeness, this space-time GIS can generate a relative physical distance chart and a virtual closeness rank chart for a selected person with his/her connected friends. This space-time GIS also includes a separate 3D plot with its three dimensions representing physical proximity, virtual closeness, and time respectively. Users can create a 3D line for each pair of people in this plot, and then explore their relationships between changes in physical proximity and changes in virtual closeness over time using a 3D cluster analysis tool. Moreover, this space-time GIS supports simultaneous representations of physical space and virtual space. Users can visualize and compare related representations and their analysis results in a single environment. This space-time GIS is useful for exploring patterns of individual activities and interactions in both physical space and virtual space, as well as the interactions between these two spaces.

## 6.2 Potential Applications of the Study

As travel is a derivative of the demand for activity participation, a better understanding of human activities and interactions in the ICT age can benefit transportation research and urban study. Activity-based approaches, which model travels and activities at the individual level, have become an important paradigm in transportation studies. The use of ICT is influencing individual activities, so disaggregate activity-based models need take into account interactions between ICT and individual activities (Miller, 2005b). The analytical frameworks and the spatio-temporal environment offered by this study can help understand human interaction patterns and time use for communication, which can potentially benefit the development of activity-based models in the ICT age. Moreover, understanding individual activity patterns and the way humans interact with others is important to urban study. Urban environments concentrate people to increase the efficiency of their encounters (Meier, 1962). The advent of ICT has changed the relationship between physical distance and human interactions. Is traditional individual accessibility still important to evaluate urban structure? The spatio-temporal exploratory environment proposed in this study can help explore the role of physical proximity in an urban environment.

The extended time-geographic framework for virtual space offers a set of representation and exploratory approaches for social network analysis. As this study demonstrates, in a social network space an individual's virtual space-time path reveals when and whom a person visited during a time period. From the pattern of a virtual space-time path, we can observe whether a person is active or not during a period of time, who are the most visited friends during a particular time period, and how a person changed his/her visit patterns over time. A virtual space-time path based on geographical locations can also illustrate the physical scope of a person's virtual communication, which is the so-called "extensibility" of a person in the ICT age (Adams, 2000). A social space-time path approximately tracks an individual's relative position within a social network over time. For example, a person may gradually move from one group to another over time. A group of people's social space-time paths visualize a dynamic social network. One importance focus of social network analysis is to dig out subgroups or communities within the entire group, and to track the changes of subgroups over time. Current approaches for such purpose focus on membership changes of a subgroup. They identify subgroups at each time interval, and then analyze the changes in each subgroup at different time intervals. Most approaches use animation to visualize dynamic social networks with a 2D map, or trace an individual's membership with a subgroup-time graph (Leydesdorff *et al.*, 2008; Reda, 2009). Social space-time paths enable researchers to identify subgroups with similar movement patterns within a social network over time. This study also presents a generalized space-time path for each subgroup, which reflects the aggregate pattern of space-time paths in a subgroup. In other words, it allows us to investigate who moves together within a social network over time. Such capability adds a new angle to investigate dynamic social networks. Accordingly, a virtual space-time path based on social space-time paths offers subgroup information to users. For instance, it illustrates which group a person's visited friends belong to. Furthermore, the space-time GIS can explore how people use ICT to maintain connections over distance. As this study demonstrates, if focusing on a group of people who stayed at the same place for a while, we can track their virtual connections to understand how they take advantage of ICT to maintain their social connections after they move apart.

The extended time-geographic framework for exploring F2F meeting opportunities offers some applications for LBS. For example, assume two people want to arrange a F2F meeting during a day. They set their planned activities in their mobile devices. Their mobile devices can send their real-time locations to the LBS server, and the LBS server will calculate their potential F2F meeting places and available meeting time according to their real-time locations and pre-set planned activities. If the service finds a person out of plan, it will alert this person of his status, and the person can choose keep plan or update plan.

## 6.3 Future Research Directions

The extended time-geographic framework about F2F meeting opportunities is a starting point to explore the complex impacts of ICT on human activities and interactions. There are a number of possible enhancements and extensions to this initial analytical framework. First of all, this analytical framework can be extended to explore F2F meeting opportunities among multiple persons (Neutens *et al*., 2008) and explicitly consider multipurpose trips (Soo *et al*., 2009). In addition, this framework can be extended to study other ICT alternatives (e.g., Internet communications via computers, mobile phones, or other mobile devices). We could, for example, examine the differences in shopping opportunities among people who have Internet access versus those who do not. Furthermore, in today's ICT world, researchers also suggest that the concept of fixed activities has become blurred (Schwanen and Kwan, 2008). Human activities tend to become more segmented and spontaneous under the additional spatio-temporal flexibilities enabled by ICT (Couclelis, 2004; Shaw and Yu, 2009). It therefore will be better to introduce various flexibility levels instead of using a binary definition of fixed versus flexible activities to represent individual activities in the analytical framework. The work of Neutens *et al*. (2007) and Kuijpers *et al*. (2010) provide useful information to pursue this research direction. Finally, the design of this analytical framework can be enhanced with empirical data. Recent studies have demonstrated that it is feasible to collect individual trajectories and phone communication records (Eagle and Pentland, 2005; Licoppe *et al*., 2008). Incorporating such datasets into the analytical framework presented in this study will not only allow us to test and improve the analytical framework but also provide empirical data for researchers to gain insight into the interactions between communications in virtual space and human activities in physical space.

In terms of the extended time-geographic framework for virtual space, this study identifies several future research directions. First, additional exploratory analysis functions can be added to this space-time GIS; for example, the cluster analysis tool will benefit from different similarity measurements for space-time paths (Shaw *et al*., 2008; Chen *et al*., 2011). In addition, some other exploratory tools may be developed to analyze virtual space-time paths. The space-time GIS developed by Yu and Shaw (2008) is able to identify co-location among different individuals in a physical space. Using the similar idea, it is feasible to develop a tool for identifying "co-location" among different individuals in a virtual space. It could be a hot spot identification tool that can detect virtual gatherings from individuals' movements in virtual space, such as an intensive discussion on an individual's webpage. Also, virtual communications related to physical movements could be identified with the semantic analysis of communication contents. For instance, if a group's discussion about a gathering is detected in a virtual space, and later a physical co-location is identified among these people, the relationships between virtual movements and physical movements could then be analyzed.

Online social networking services such as Facebook and Twitter have already become a key social media. More studies are needed to track and understand human interactions in social networking services, as well as the way they are affected by the physical world. This study collected a small group's communication data in a social network space, and offered a pilot research demonstration in the process. The analysis results of the pilot study did not show strong constraints from physical proximity on social closeness in virtual space. On the contrary, most of the participants showed positive attitudes toward maintaining their connections with alumni on social networking websites over distance. In addition, this study also found time zone difference has impacts on with online communication time-lag. As with any case study, the specific findings pertain only to the selected group of subjects. This pilot study collected data based on the author's social network. Some studies have already proved the feasibility of developing an online communication dataset for a large population (Lewis *et al.*, 2008). Collecting a larger sample and drawing more general conclusions is a worthwhile future research.

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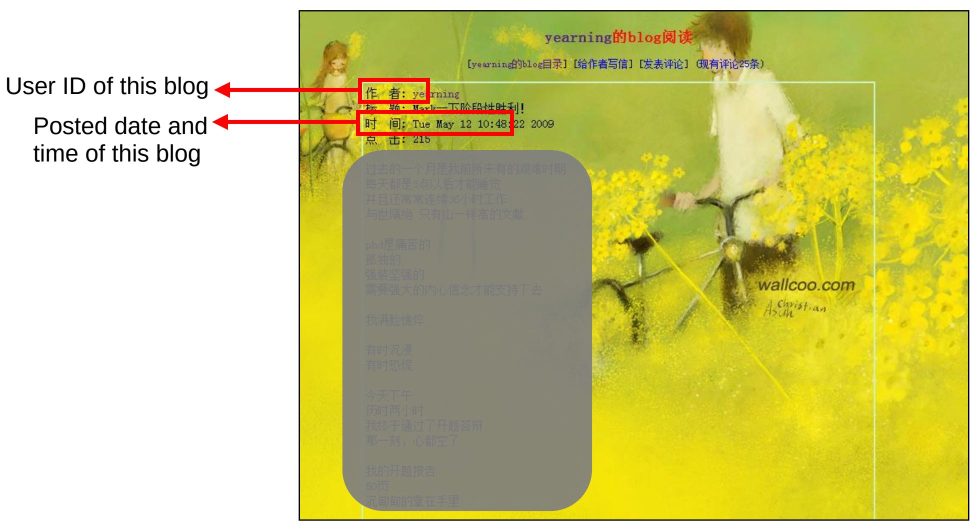
# APPENDIX

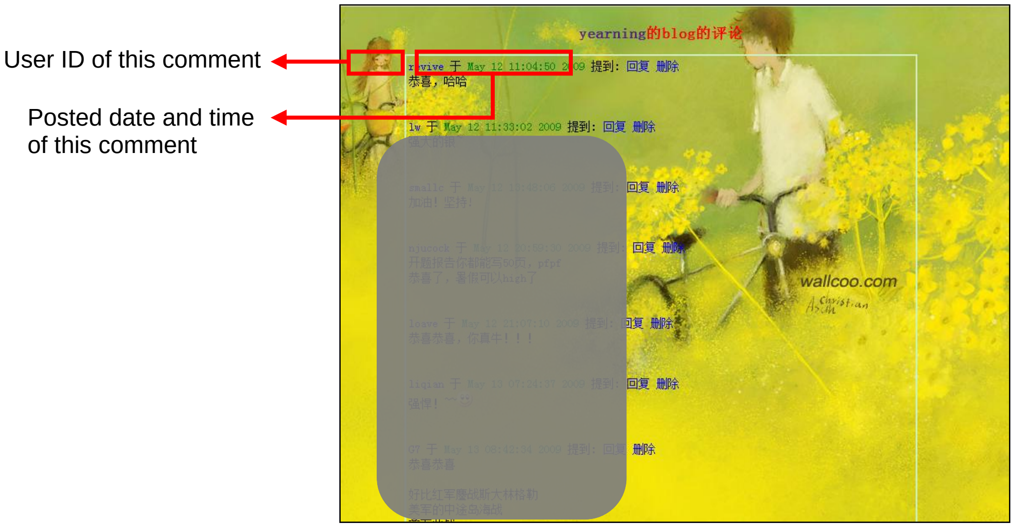
# Appendix A: Examples of Social Networking Websites

An example of a personal blog list on Lily BBS

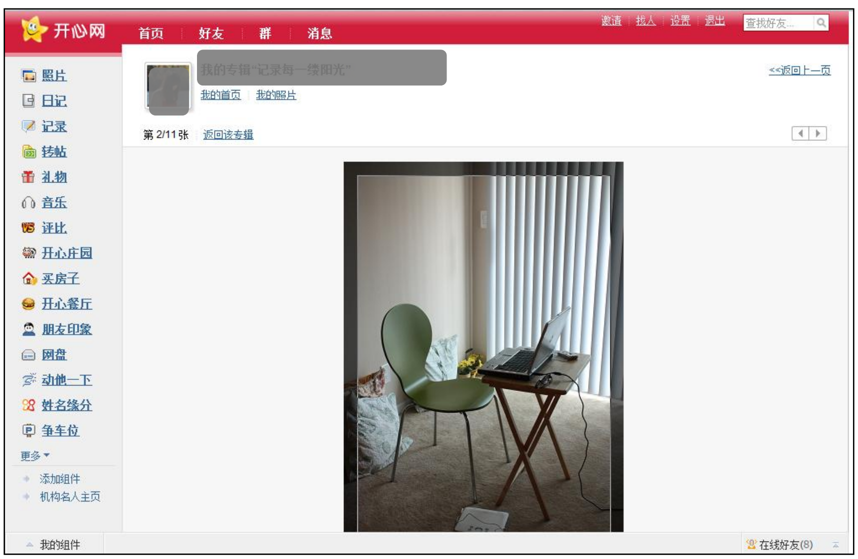
An example of a blog page on Lily BBS



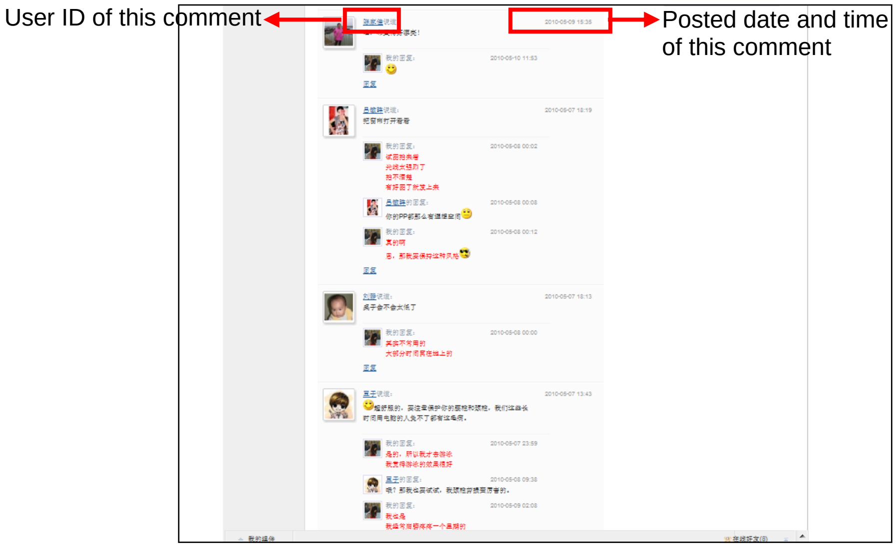
. An example of a comment page of a blog



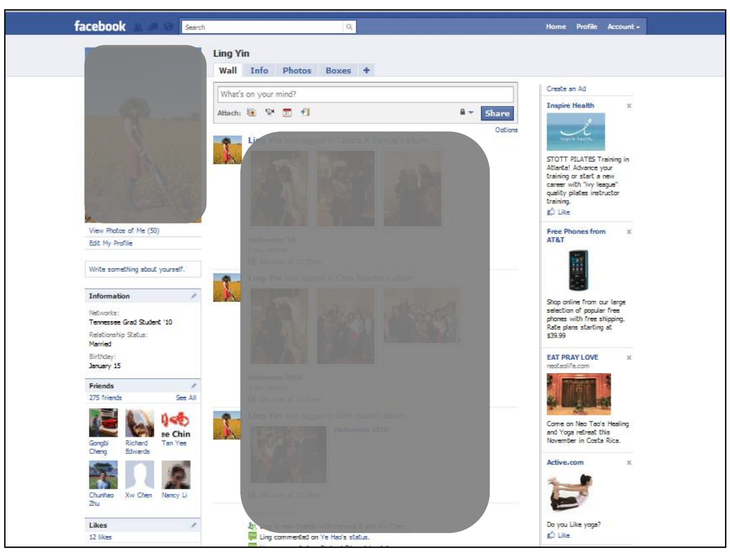

An example of a picture post on Kaixin website



An example of a comment page on Kaixin website




An example of a personal page on Facebook



An example of a user’s activities on Facebook

# Appendix B: Online Survey

Page 1

ICT and Social Network

Exit this survey

**Informed Consent 参与调研同意书**

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Project Title: Spatial-temporal constraints on social networks in the age of information and communication technologies
Principal Investigator: Ling Yin

研究项目名称：信息时代下社交网络的时空约束
研究者：尹凌

You are invited to participate in a research study on social networks and information and communication technologies (ICT), specifically on relationships between online communications among people and their spatial-temporal relationships in physical space (e.g., physical distances between people). There is a growing body of literature on ICT and social networks, but little work has been done to assess the spatial-temporal constraints on social networks in today's ICT society. This project addresses that gap. The researcher is interested in the following questions: What are the relationships between people's geographical distances and their virtual distances in social networking websites; How can we visualize virtual distances between people in a geographical information system (GIS) as well as the dynamics of web-based social networks over time; What approaches can detect spatial-temporal relationships in physical space from virtual communication data. The researcher will collect data from her classmates in the Department of Geography at Nanjing University. Data includes communication records from several major social networking websites, residency places, and habits of using ICT to maintain social networks. The time span of data is five years.

亲爱的朋友，您被邀请参与一项有关社交网络与信息通讯科技（ICT）的研究项目。该项目研究人们的网络通讯与他们在物理空间上的时空关系之间的联系。近年来关于ICT和社交网络的研究日益增加，但是分析和评价当前ICT社会中社交网络的时空约束的研究却鲜有见到。该研究项目的目标便是弥补这个空缺。研究者将对以下问题进行探索：人们的实际地理距离与他们在社交网站上的虚拟距离之间存在着何种关系；如何在地理信息系统（GIS）中可视化人们的虚拟距离以及虚拟社交网络的动态变化；何种方法可以从虚拟交流信息中探测到物理空间中人们的时空关系。研究者将收集她在南京大学地理系的部分同学的数据。这些数据包括参与者在几个主要的社交网络上的交流信息，参与者的搬迁史，以及参与者使用ICT维持社交关系的习惯。数据的时间跨度是从2005年1月1日至今。

INFORMATION ABOUT PARTICIPANTS' INVOLVEMENT IN THE STUDY

Participation in the study is voluntary. As a participant, you will take an online survey, and after one month take another online survey which is designed based on the analysis results from the first survey. Each online survey will take between 10 and 20 minutes to complete. The researcher will also collect your communication data from the three social networking websites (Lily BBS, Kaixin website, and Facebook). The data to be collected are communication histories that are publicly accessible to your friends, including anonymous IDs of participants, date and time of their posts, and date and time of their comments. NO communication contents will be kept. The research will only include records of participants. Communication records of other users who made comments on a participant's page will be excluded. The database will be stored on the researcher's password-protected hard drive and password-protected laptop, and the hard drive will be kept in a locker in the researcher's office at the University of Tennessee in Knoxville. If you agree to provide your relevant information and communication data on your social networking websites, please check the "agree" checkbox at the bottom of this document.

有关参与此项研究的基本信息

这项研究的参与是自愿性质的。作为一个参与者，您接下来将完成一份在线问卷，随后一个月左右会完成另一份根据第一份问卷结果产生的在线问卷。每一个在线问卷将会花费10到20分钟时间。与此同时，研究者会从三个社交网站上收集您的交流信息，包括南京大学小百合Blog、开心网（www.kaixin001.com）、和Facebook。所有收集的信息均是您的社交网站朋友可以看到的公开信息，包括ID、发帖的时间、评论人的ID、和评论发布的时间。所有交流内容将不会被收集。研究者也将只保留参与者的数据。除参与者以外的评论信息将会被删除。数据库将会存储在研究者密码保护的硬盘和笔记本上。硬盘将会被锁在研究者在田纳西大学的办公室内。如果您同意提供您在以上三个社交网络上的交流信息，请在同意书末尾选择"同意"。

RISKS

Your risks in participating in this study are minimal. You can choose to not answer any question(s) for any reason in the online survey and can decide to no longer participate at any time. You will be represented by pseudonyms in this research. Your history of places of residence at city level and time of your online communication that are publicly available to your friends may be included in the researcher's dissertation, maps, or academic articles, but your identifiable information will be eliminated in any publications.

风险

您参与这项研究的风险极小。您可以选择对任何在线问题不作答，也可以在任何时候决定中止参与研究。在整个研究过程中，您的个人身份将会被假名代替。您的居住地点和您在以上网站上交流的时间有可能会被包括在研究者的博士论文、地图、或者学术文章里，但是您的所有可识别身份的信息将会被完全排除。

BENEFITS

This research will contribute to the growing literature on ICT and social networks. Also, it will add to our understanding of the interactions between communications in physical space and virtual space. Finally, the space-time GIS and its exploratory functions will provide researchers tools for analyzing human activities in the modern hybrid physical-virtual space. At your request, the researcher will email a copy of articles with results from this research project.

利益

这项研究将会为日益增长的关于ICT与社交网络的文献做出贡献。同时它也会增加我们对物理空间交流与虚拟空间交流的相互作用的理解。由此而开发的时空GIS和相应的探索性分析功能也将为广大研究者提供分析人类在现代信息空间中活动的工具。如果您有兴趣，研究者将会发给您基于此研究结果的论文。

CONFIDENTIALITY

To protect your privacy, the researcher will use a pseudonym to represent each participant. Your personal information (e.g., gender, age) will not be linked to the pseudonymous persons. No communication contents will be collected. Data will be stored securely at the University of Tennessee and will be made available only to the researcher.

保密性

为了保护您的隐私，研究者将会使用假名来表示每一个参与者。您的个人信息（例如，性别、年龄等）将不会与使用假名的人物进行联系。任何交流内容将不会被收集。数据将会被安全存放于田纳西大学，并且只供研究者一人使用。

CONTACT INFORMATION

If you have questions at any time about the study or the procedures, you may contact the researcher, Ling Yin, at the Department of Geography, 304 Burchfiel Geography Building, University of Tennessee, Knoxville, TN 37996 (telephone: (001) 865-385-3765 and e-mail: lyin@utk.edu). If you have questions about your rights as a participant, contact the Office of Research Compliance Officer at (001) 865-974-3466.

联系信息

如果您在任何时间有任何问题，请及时联系研究者：Ling Yin, the Department of Geography, 304 Burchfiel Geography Building, University of Tennessee, Knoxville, TN 37996。电话：(001) 865-385-3765。电子邮件：lyin@utk.edu。如果您对参与者的权益有任何疑问，请及时联系研究督察办公室：(001) 865-974-3466。

PARTICIPATION

Your participation in this study is voluntary; you may decline to participate without penalty. If you decide to participate, you may withdraw from the study at anytime. If you withdraw from the study before data collection is completed, your data will be destroyed.

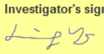
参与

您对本研究的参与完全是自愿的。您可以在任何时候自由退出。如果您决定退出参与此项研究，您的所有数据将会被销毁。

该项目通过了田纳西大学人文研究部门的审查，并且将受到研究监督部门的追踪与督察，所以请对数据采集渠道、数据保存、以及数据保密性放心！

万分感谢您对该研究的支持！

**Investigator's signature：**



Date: 12/11/2010

------------------------------------------------------------

**Consent**

☐ I have read the above information. By checking this box, I agree to participate in this study. And I allow the Principal Investigator to collect my online communications data on Lily BBS, Kaixin website, and Facebook, which is publicly available to my connected friends on these websites.我已阅读以上信息。我同意参与此研究项目。同时我允许该项目研究者收集我在南京大学小百合Blog、开心网（www.kaixin001.com）、和Facebook上对我朋友公开的信息。

☐ I request a copy of articles with results from this research project. 我要求收到基于此项研究结果的学术文章。

**Participant's signature 参与者签名（请输入您的姓名，中英文皆可）**

**Date 日期**

请填写当前日期（月/日/年） MM / DD / YYYY

Next

# Page 2

ICT and Social Network — Exit this survey

**Part One: History of your residency places 您的居住史**

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Please enter your residency places in chronological order beginning from Jan 1, 2005. If you do not remember the exact date of a move, please approximate.
请从2005年1月1日起按照时间顺序填写您过去五年的居住史。您只需要填写不同城市的搬迁记录。不包括短暂出差或者旅游的地方。 请从左向右，从上至下依次填写 （中英文皆可）。

| Where have you lived since 01/01/2005 to 11/31/2010? (City, Province/State, Country) 从2005年1月1日至2010年11月31日，您在哪些地方居住过？(请填写：城市，省份/州，国家) | Approximately when did you move into this location? (MM/DD/YYYY) 您大概什么时间搬到这个地方的？ (请填写：月/日/年) 如果不记得确切时间，请填写大概时间。 | Approximately when did you leave this location? (MM/DD/YYYY) 您大概什么时间搬离这个地方的？ (请填写：月/日/年) 如果不记得确切时间，请填写大概时间。 |
|---|---|---|
| 1.Location | Date | Date |
| 2.Location | Date | Date |
| 3.Location | Date | Date |
| 4.Location | Date | Date |
| 5.Location | Date | Date |
| 6.Location | Date | Date |

**If you lived in more than six places in the last five years, please continue your answer here:**
**如果您在过去五年的居住地超过六个，请在此继续按照上述格式填写：**

Page 3

ICT and Social Network

Exit this survey

**Part Two: Habits of using ICT to maintain social networks (Page 2)**

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**How do you contact your classmates living IN OTHER CITIES BUT STILL IN THE SAME COUNTRY by each means after your graduation from Nanjing University?**
**通常您如何联系在“同一国家其他城市”的校友？ 请按选择各种联系方式的使用情况。**

| | Most used 最常用 | Second most used 次常用 | Occasionally used 偶尔使用 | Never used 从不使用 |
|---|---|---|---|---|
| Social networking websites (e.g., NJU Lily BBS, Kaixin website, Facebook) | | | | |
| Instant message software (e.g., QQ, MSN, Skpye) | | | | |
| Email | | | | |
| Telephone call/Text message | | | | |
| Face-to-face communication | | | | |

Other (please specify) 补充说明

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ICT and Social Network

Exit this survey

**Part Two: Habits of using ICT to maintain social networks (Page 3)**

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**How do you contact your classmates living IN OTHER COUNTRIES by each means after your graduation from Nanjing University?**
**通常您如何联系在“其他国家”的校友？ 请按选择各种联系方式的使用情况。**

| | Most used 最常用 | Second most used 次常用 | Occasionally used 偶尔使用 | Never used 从不使用 |
|---|---|---|---|---|
| Social networking websites (e.g., NJU Lily BBS, Kaixin website, Facebook) | | | | |
| Instant message software (e.g., QQ, MSN, Skpye) | | | | |
| Email | | | | |
| Telephone call/Text message | | | | |
| Face-to-face communication | | | | |

Other (please specify) 补充说明

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**Part Two: Habits of using ICT to maintain social networks (Page 4)**

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**How do you use the three social network websites (Lily BBS Blog, Kaixin website, or Facebook)? Please check any uses that apply.**
**您使用这三种社交网络的目的有哪些？ 请选择所有符合的选项。**

- [ ] Post your updates (e.g., status, pictures, diaries) 发布自身状态 （例如，状态，照片，日记等）
- [ ] Check your friends' updates (e.g., status, pictures, dairies) 查看朋友的更新 （例如，状态，照片，日记等）
- [ ] Have business talk with your friends 进行公务交流
- [ ] Have casual talk with your friends 闲谈
- [ ] Organize events (e.g., Hold a party) 组织活动 （例如，组织聚会）
- [ ] Browse latest news 查看新闻
- [ ] Play online games 玩在线游戏

Other (please specify) 补充说明

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ICT and Social Network | Exit this survey

**Your basic information**

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您已完成本次在线调查。请填写以下基本信息（中英文皆可）。您的基本信息将不会被公布，并且只由研究者一人保密保存。

**This information will only be used by the researcher. Your personal information and identity will not be released to others.**

Name

Gender

Age

Major at Nanjing University

The year of entering Nanjing University

The year of leaving Nanjing University

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# VITA

Ling Yin was born and raised in Chongqing, the People's Republic of China. She moved to Nanjing City for her undergraduate study in 1999, and then received a Bachelor of Sciences degree and a Master of Sciences degree in geography at Nanjing University in 2003 and 2006. In the summer of 2006, she came to the U.S. and entered the geography department at the University of Tennessee, Knoxville, where she completed her Doctor of Philosophy degree in the summer of 2011. Ling Yin is a member of AAG and CPGIS. She has been a reviewer for the journal of *Transactions in GIS*. Her research interests include spatio-temporal data mining, space-time GIS, time geography, ICT and individual activities, and activity-based approach.