egoSlider: Visual Analysis of Egocentric Network Evolution

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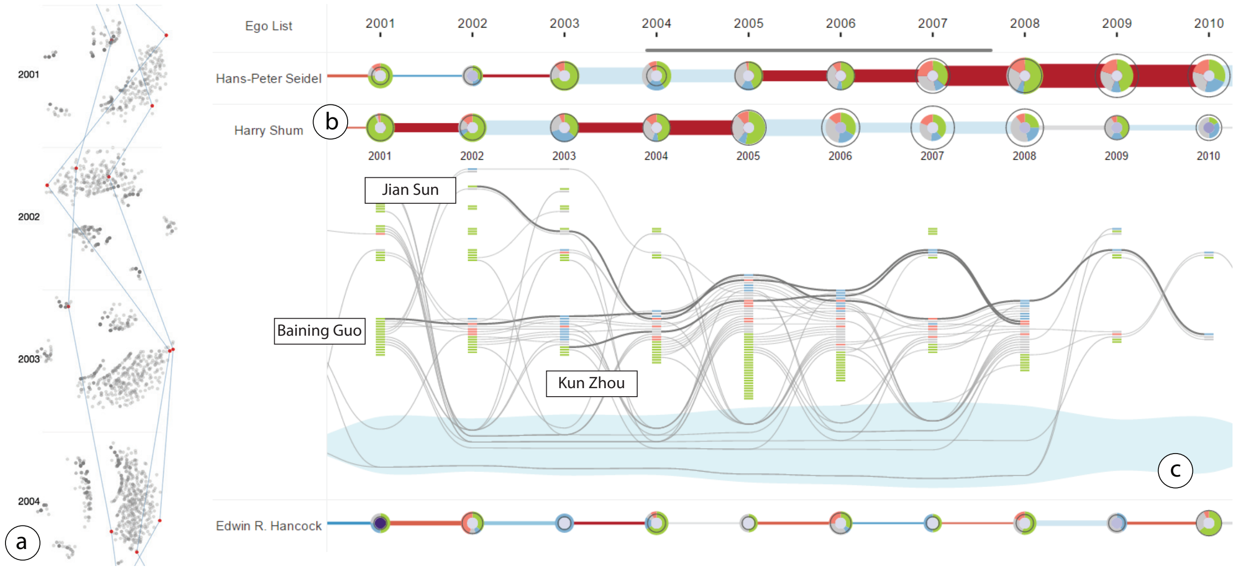

Fig. 1. Exploring the ego-network evolutionary histories of several prestigious researchers in the fields of computer graphics, computer vision, and visualization based on the DBLP collaboration network data. General patterns of all researchers' ego-networks (such as clusters and outliers) are revealed in a) the overview. Overall variations of one's ego-network characteristics (such as alter numbers and densities) can be learned by viewing the snapshot glyph and transition glyphs in b) the timeline-based visualization. Detailed structures of alters in the ego-networks (such as different connected components) and their temporal relationship information with the ego are further visualized in c) the expanded timeline view. For example, we can see that Harry Shum's ego-network grew significantly from 2001 to 2005 (from the circle sizes), and meanwhile his collaborators converged from multiple connected components into one after 2004 (when he became a Managing Director at MSRA). Three of his long-term collaborators can also be identified.

Abstract—Ego-network, which represents relationships between a specific individual, i.e., the ego, and people connected to it, i.e., alters, is a critical target to study in social network analysis. Evolutionary patterns of ego-networks along time provide huge insights to many domains such as sociology, anthropology, and psychology. However, the analysis of dynamic ego-networks remains challenging due to its complicated time-varying graph structures, for example: alters come and leave, ties grow stronger and fade away, and alter communities merge and split. Most of the existing dynamic graph visualization techniques mainly focus on topological changes of the entire network, which is not adequate for egocentric analytical tasks. In this paper, we present egoSlider, a visual analysis system for exploring and comparing dynamic ego-networks. egoSlider provides a holistic picture of the data through multiple interactively coordinated views, revealing ego-network evolutionary patterns at three different layers: a macroscopic level for summarizing the entire ego-network data, a mesoscopic level for overviewing specific individuals' ego-network evolutions, and a microscopic level for displaying detailed temporal information of egos and their alters. We demonstrate the effectiveness of egoSlider with a usage scenario with the DBLP publication records. Also, a controlled user study indicates that in general egoSlider outperforms a baseline visualization of dynamic networks for completing egocentric analytical tasks.

Index Terms—Egocentric network, dynamic graph, network visualization, glyph-based design, visual analytics

1 Introduction

Nowadays, social network analysis has become an important approach for investigating information flows and people relationships in our societies [7]. Sociologists, psychologists, and anthropologists have mainly focused on two aspects of social networks: sociocentric analysis that quantifies relations of a large group of people, and egocentric analysis that studies dynamics between a specific individual, called *ego*, and people connected to the ego, called *alters*. The latter type of networks, often named *personal networks* or *ego-networks*, indicates how an individual is tied to an outside social world. Understanding how such networks evolve over time can provide huge insights to miscellaneous domains. For example, researchers can better comprehend different communication behaviors in various online social spaces by analyzing ego-networks [30]; medical experts find that one's health condition is strongly associated with many ego-network related factors (e.g., friend degrees) [44]; analysts in management, business intelligence, and information security can make more informed decisions by identifying the most influencing people in social networks and how they affect others along time [2, 18, 39].

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Social network researchers have developed extensive analytical methods to measure and model various aspects of ego-networks, such as statistical analysis, predicting ties, and detecting alter communities [7, 11, 37, 42, 43]. However, few are able to capture the evolutionary patterns of ego-networks due to the highly dynamic and complex nature, which requires human supervision in the process of exploration and analysis. Along an individual's life, relational ties to alters intertwine: some relationships emerge and some fade away, some become stronger and some turn distant [17]. Not only do the connections between the ego and alters vary in time, but also the dynamics among different alters. There exists a series of questions need to be addressed, for example, when and how new relations come into being, how the strengths of relations change over time and affect each other, and how the alter community structures evolve during a timespan.

Although many dynamic graph visualizations have been proposed (e.g., [8, 9, 53]), they mainly focus on tracking changes of the entire graph rather than the characteristics of ego-networks. Some methods that attempt from the egocentric point of view (e.g., [28, 46, 50]) merely visualize the ego-alter relationships, but omit the connection strengths and inter-alter relationships, making it impossible to answer some alter-related questions, such as insights about alter communities.

To address the above concerns, we propose an interactive visualization system, called *egoSlider*, for exploring, comparing, and analyzing ego-network evolution. egoSlider provides a holistic picture of the dataset through three major views, allowing users to browse ego-networks at various levels of scale. 1) An overview shows overall temporal patterns, such as clusters, of all individuals' ego-networks in the database (Fig. 1-a), where users can further dive into different regions of interests. 2) A glyph-based timeline visualization summarizes one's ego-network evolution with critical statistical features such as alter numbers, densities, and overall changes of ego-alter relation strengths (Fig. 1-b). Comparative analysis of different people's dynamic ego-networks can be easily achieved by viewing multiple timelines. 3) A detailed view of a person's ego-network timeline can be further revealed for browsing dynamic structures of alters in the ego-networks, such as tracing the relationship with a specific alter along time, and discovering alter communities (Fig. 1-c). These three views are seamlessly coordinated with a rich set of interactions, supporting a smooth navigation of the dataset and multi-scope insight discovery in ego-network analysis. egoSlider also incorporates several analytical abilities to filter the data, extract ego-network features, and conduct similarity measurement of different ego-networks.

Our main contributions in this paper include:

- An interactive visualization system, named egoSlider, that enables users to explore, compare, and analyze dynamic ego-network evolutionary trends and patterns;
- Novel glyph designs for summarizing critical characteristics of one's ego-networks, and a new timeline visualization for tracking the variations of ego-alter connection strengths and alter-alter relationship structures;
- A usage scenario with real dataset and a controlled user study that demonstrate the effectiveness and usefulness of egoSlider.

2 Related Work

2.1 Egocentric Network Analysis

Ego-network has been extensively studied in the field of anthropology and sociology for a long time. When studying ego-networks, most of the works focus on the 1-level ego-network formed by the ego and its 1-degree alters, i.e., the ego's directly connected friends (e.g., [2, 4, 24, 45]); and few study ego-networks containing the ego's more distant connections (e.g., [33] discusses 2-level ego-networks including 1- and 2-degree alters). Major literature in those fields falls into two categories: *microscopic* level and *macroscopic* level analysis.

Microscopic level analysis studies how structures and attributes of ego-networks affect the ego's behaviors. One major focus is to investigate correlations between the topology of ego-networks and the ego's characteristics. For example, the structural hole theory indicates that an individual may gain strategic advantages over others when his or her alters are highly separated and have a relatively low connection density [2, 4, 24]. Romantic relationships between two people can be recognized based on what extent that their mutual friends are well-connected [11]. Another approach focuses on the relation type and strength between the ego and alters as well as their impacts to the ego. Studies show that the existence of stable ego-alter relationships plays a fundamental role in an individual's life cycle [25]. There are also some work targeting at the dynamic process of relationship building, which attempts to answer questions related to where, when, and how relations come into an ego-network [33, 36]. Prell described three major properties that are typically studied in ego-network analysis: the number of alters (*degree*), the strengths of ties connecting the ego and alters (*closeness*), and the number of interconnections between alters (*transitivity*) [45].

Macroscopic level analysis looks at the overall patterns in a subgroup of egos or the entire network. Many researchers have attempted to analyze structural properties of ego-networks. Arnaboldi et al. confirmed that certain attributes of online ego-networks appear to be similar to those found "offline", including the number of alters and the relation strength distribution [7]. Network size was found having a large impact on compositional properties of the network and ego characteristics [48]. Lubbers et al. suggested that the persistence of ties was related to tie strength, network density, and other alter attributes [41]. Moreover, there is some work that characterizes ego-networks into various categories, revealing different social communication patterns [14, 30]. Dynamic evolution of ego-networks has also been of great interests by researchers. For example, Arnaboldi et al. found that people in Twitter have highly dynamic ego-networks with a large percentage of weak ties and high turnover [6].

Quantitative measurements of graphs are also related to our work. Most proposed metrics focus on static graphs (such as node degrees, betweenness, etc.). A few of them have been extended for measuring dynamic graphs, although they are not specialized for dynamic ego-networks. For example, time-scale degree centrality considers both presence and duration of links [52]; and change centrality compares two graphs based on change events such as added, removed, and remained links [29].

The design and development of our egoSlider system stem from the observations and analysis of the above literature. Based on these studies, we derive metrics that characterize ego-network evolution, and distill our research questions and design goals in Sec. 3.

2.2 Dynamic Network Visualization

Many visualization techniques have been proposed to address the dynamic evolving nature of network data. Major methods include using animated transitions, showing network variations along timelines, and a hybrid of the two. A comprehensive survey can be found in [12].

Animation-based approaches were first used by Eades and Huang to show changes between time steps of dynamic networks [27]. Staged transitions have been widely used to reduce users' visual effort for identifying and understanding the temporal changes [8, 21, 31]. Some change highlighting techniques are also applied in those staged animations [8]. Although animation is an effective way to decrease the complexity of dynamic network evolution, it may lead to a high cognitive load [5]. It is also difficult for users to track the transitions when comparing multiple networks at the same time.

One type of timeline-based techniques leverages a series of node-link diagrams to represent networks at different time steps, such as small multiples of network snapshots juxtaposed to each other [51]. Itoh et al. extended this idea into 3D spaces so that users can observe global differences between graphs more easily [38]. Some other methods put nodes on a vertical axis, which can better utilize the screen real estate and highlight the changes of links over time [23, 32, 53]. We adopted a similar design to visualize the evolutions of alter connections in ego-networks. Another approach is based on a matrix-based representation of networks, where the temporal information is encoded as an intra-cell glyph-based timeline, such as simple bar charts or Gestaltlines [20, 22]. However, since the minimum matrix cell size is restricted by the intra-cell visualization, such methods are not scaled for large networks. Besides, some works visualize the adjacency list over time which is suitable for analyzing certain tasks in dynamic graphs such as exploring the overall link change patterns [34, 47].

There exist a few visualization systems using a hybrid approach, i.e., combining the animation-based and timeline-based techniques together to achieve better performance for certain tasks. DiffAni supports flexible interactions that allow users to divide the whole graph sequence into several aggregation views including diff tiles, animation tiles, and small multiple tiles [49]. Beck et al. used a rapid serial visual presentation approach to animate a timeline of graphs at a high frequency in order to address the scalability problem [13].

However, all the above dynamic graph visualization techniques aim to show variations of the entire graph. Egocentric analysis focuses on specific sub-networks, where particular connections, such as ego-alter and alter-alter relationships, are more concerned rather than the overall topology. Also, it is difficult to use the above techniques to achieve visual comparisons of different ego-networks, since they all focus on one dynamic graph.

There have been several attempts to help users understand network data from the egocentric perspective. Many approaches adopt a radial layout where alters are positioned around the ego and the temporal relation information is encoded by the radius length [19, 28, 46]. On the other hand, Shi et al. proposed a 1.5D visual design to reveal the dynamic pattern of an ego-network [50]. However, many essential aspects of ego-networks are missing in those visualizations, such as relation strength changes between an ego and its alters, and inter-alter connection variations over time. Compared with these approaches, egoSlider covers a much wider range of important properties for analyzing ego-network evolution.

3 Analytical Questions

Experts with different backgrounds may have various interests on certain ego-network features. For example, anthropologists could pay more attention to kinship relations which is related to a set of alters who hold strong ties with the ego; health experts could focus on an ego's pro-social behaviors that can be defined as a quantitative ego attribute. We aim to design egoSlider as a general-purpose visual analysis tool that benefits users from different domains with deeper understandings of ego-network evolution. Although Ahn et al. presented a comprehensive task taxonomy for network evolution analysis [3], it is not specialized for ego-network analysis which demands specific attributes such as tie strength to be explicitly described in the tasks.

We choose the approach of first deriving analytical tasks from the literature and then validating them with experts. We selected 38 dominant ego-network related publications across different domains (Sec. 2.1), then classified them into two categories: *macroscopic* level and *microscopic* level. Next we derived a series of key analytical questions that users often need to answer when studying dynamic ego-networks. We then conducted in-depth interviews with two experts in graph mining. They helped us refine the questions, and suggested adding an additional *mesoscopic* level to capture the overall comparison of ego-network evolution of different individuals, because it is a common scenario in their daily research.

In this paper, we focus on the visualization of at most 2-level ego-networks (i.e., containing the ego, and its 1- and 2-degree alters), which is related to a vast majority of studies in the literature. Unless specifically stated, when mentioning the ego's alters, we refer to its 1-degree alters; when mentioning one's ego-network, we refer to the 1-level ego-network. The analytical questions are described below.

The **macroscopic** level questions aim to obtain a whole picture of all ego-networks from a large group of people [6, 14, 30, 48]:

- Q1 *What are the overall patterns of a large group of people's ego-networks at each time step?* Are there any clusters of people with similar ego-networks? Are there any outliers?
- Q2 *What are the evolutionary trends of a large group of people's ego-networks?* Do they share a common evolutionary path? Does a number of people's ego-network evolution always keep structurally similar along time, or become different sometimes?

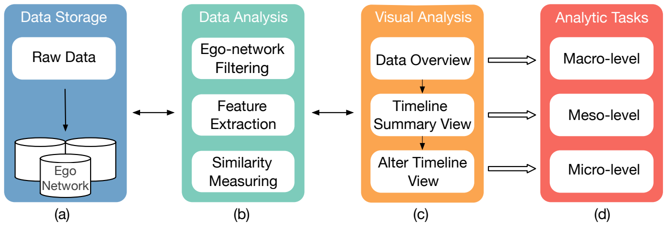

Fig. 2. The overview of the egoSlider visualization pipeline. a) The ego-network structures are extracted from the raw data and stored into MongoDB. b) The data analysis module incorporates several analytical methods to process the dynamic ego-network sequences. c) Users can interactively navigate through three major views to perform visual analysis of the data. d) Each view in egoSlider is aimed to address a different level of ego-centric analytical tasks.

The **mesoscopic** level questions focus on the overall comparison among a set of individuals' ego-networks [11, 25, 33]:

- Q3 *What are the general similarities between multiple people's ego-networks along time?* Do their ego-network sizes increase or decrease simultaneously? Do they all tend to meet more new alters in a specific time period? Are there any different trends in terms of alter numbers?
- Q4 *What are the differences between multiple people's ego-networks at a specific time step?* Do they hold the same alter density? Do they have a similar number of 1-degree alters? Do the alters share common attributes? How about 2-degree alters?

The **microscopic** level questions mainly study the detailed behaviors of a particular person's ego-networks [2, 4, 24, 36]:

- Q5 *How does the number of an ego's 1- or 2-degree alters change over time?* Is it increasing or decreasing? Is there a periodical pattern? Are there any alter number spikes? Are the 1- and 2-degree alter volumes correlated?
- Q6 *How do the tie strengths between the ego and its alters evolve along time?* Do the alters who share stronger ties with the ego also preserve longer relations? Does the tie strength become weaker and weaker before an alter leaves the connection? Do the majority of alters follow the same tie strength evolutionary pattern?
- Q7 *How are the alters of an ego connected over time?* How many connected components can be divided at different time steps? What is the alter flowing trend among the connected components in a specific time span? Do the alters tend to diverge into different small subgroups or to merge into a highly connected community?
- Q8 *How do new relations come into being?* Is a new alter also a 2-degree neighbor of the ego previously? If so, who are the bridges between the new alter and the ego? Is a new alter the ego's previous alter long time ago? If so, where did this alter go? Staying relatively close to the ego as a 2-degree neighbor, or much farther away?

4 System Overview

Motivated by the above analytical questions, we designed egoSlider allowing users to explore and analyze dynamic ego-network data at three different scales: the overall patterns of all people's ego-networks with a *Data Overview*, the similarities and differences of ego-networks among individuals of interest with a *Summary Timeline View*, and the detailed information of a person's ego-network history from multiple perspectives with an *Alter Timeline View*.

The whole egoSlider system consists of three major components: data storage and preprocessing module, data analysis module, and visual analysis module, as shown in Fig. 2. The data storage and processing module extracts ego-network structures from raw datasets such as citation networks, communication networks, and online social networks. We used MongoDB as our data storage software since it can provide a highly flexible and customizable data schema. The data analysis module performs data filtering of the extracted ego-networks, and further characterizes them with essential numerical features for measuring graph similarities. It thus allows typical computational and visual methods, such as multidimensional scaling (MDS) [40], to be used to reveal the distributions of the entire dataset and detect common patterns of ego-network evolutionary trends. Both the above two modules were developed in Python by leveraging Flask, a Python web framework, to build the backend. Three major views are integrated in the visual analysis module, i.e., the front-end visualization, to support different levels of analytical tasks with smooth interactions. We implemented the visual analysis module using AngularJS and D3.

5 Data Analysis

In this section, we introduce our analytical approaches used in the data analysis module (Fig. 2-b). We first describe a formal data model for dynamic ego-network datasets, and then a set of numerical metrics for measuring the similarity between two ego-networks.

5.1 Data Model

In egoSlider, we consider dynamic egocentric network data as a sequence of local friendship networks with time steps. Particularly, an ego-network at time step t is modeled as an undirected weighted graph $G_u^t = (V_u^t, E_u^t)$ centered at the ego actor u. The graph nodes, V_u^t, consist of the ego u and n_u^t active alters of u, denoted as $V_u^t = \{u \cup v_u^{ti} | 1 \leq i \leq n_u^t\}$. Each edge $e_j \in E_u^t \subseteq V_u^t \times V_u^t, 1 \leq j \leq |E_u^t|$ has a weight $w_{e_j} \in \mathbb{R}$. The difference between G_u^t and a general graph is that there are exactly n_u^t edges $F_u^t = \{(u, v_u^{ti}) | 1 \leq i \leq n_u^t\} \subseteq E_u^t$ which connect the ego u and all of its alters. Thus, the dynamic egocentric network of the ego u can be represented as $\Gamma_u = \{G_u^1, G_u^2, ..., G_u^T\}$, a sequence of T graphs where $G_u^k, 1 \leq k \leq T$ shares the same ego u.

5.2 Graph Similarity

Based on the studies about ego-network and general graph analysis (e.g., [11, 14, 15, 24]), we derive the following essential metrics to characterize an ego-network. We describe those metrics using the data model introduced above:

- Number of alters of the ego u: $n_u^t = |V_u^t - \{u\}|$;
- Density (or clustering coefficient) of the ego u's ego-network: $den(G_u^t) = \frac{L}{n_u^t(n_u^t - 1)/2}, L = |E_u^t| - n_u^t$, where L denotes the number of edges between the alters;
- Average tie strength (or weight) between the ego u and its alters: $avg(w_{e_i}), e_i \in F_u^t$;
- Number of edges between the alters of the ego u: $|E_u^t - F_u^t|$;
- Number of 2-degree alters of the ego u: $|N(G_u^t)| = |\{w | w \in V_v^t, v \in V_u^t, w \notin V_u^t\}|$;
- Average alter number of the alters' themselves ego-networks: $avg(n_v^t), v \in V_u^t - \{u\}$;
- Number of outgoing edges from the ego u's ego-network: $|E(G_u^t)| = |\{e_{v,w} | e_{v,w} \in F_v^t, v, w \in V_u^t, w \notin V_u^t\}|$.

Leveraging the above metrics, we form a feature signature vector for each ego-network and adopted the Canberra Distance proposed in [15] to compute pairwise similarity or distance between ego-networks: $dCan(P,Q) = \sum_{i=1}^{n} |P_i - Q_i| / (P_i + Q_i)$, where P and Q represent the feature signatures of two ego-networks.

We choose this signature similarity based approach because it is less expensive to compute while providing a customizable graph comparison criteria [15]. Also, the Canberra Distance measurement is sensitive to small changes and normalizes the absolute difference of individual comparisons, which benefits users with the detection of clusters and outliers of ego-networks at different time steps.

6 Visual Design

The main goal of egoSlider visualization design is to provide intuitive visual metaphors supporting the analysis of dynamic ego-network datasets according to the previously introduced questions at three different scopes (Sec. 3). We aim to offer effective visual summaries of important ego-network characteristics to allow temporal pattern discovery at different scales, for example, clusters and outliers detection at the macroscopic level, overall ego-network topology comparison at the mesoscopic level, and detailed alter information browsing at the microscopic level. In addition, a rich set of user interactions is needed in egoSlider to support a holistic analysis of dynamic ego-networks across all levels of tasks.

In this section, we first provide an overview of the egoSlider interface, then introduce the visual encodings of individual views as well as the design alternatives we considered, and finally present the user interactions equipped in egoSlider.

6.1 egoSlider Interface

As shown in Fig. 3, the interface of egoSlider consists of four major UI components: a) a Data Overview panel showing the overall patterns of the entire dataset of many people's ego-network evolutionary histories, b) a detailed view canvas displaying the Summary Timeline Views of selected individuals' ego-networks and their fully expanded Alter Timeline Views on demand, c) a control panel displaying all the egos from the dataset in a table with interactive searching, and d) a toolbar on the top where users can select the dataset to visualize and toggle the overview panel and the control panel.

6.2 Data Overview

We designed the Data Overview to illustrate the overall ego-network patterns (Q1 and Q2). By using the ego-network similarity measurement in Sec. 5.2, for each time step, we used MDS layout [40] to generate the distribution of ego-networks. Different from traditional MDS-based graph layout where closer nodes share more common neighbors, closer ego-networks here express more similarity based on the metrics. As shown in Fig. 1-a, each ego-network is represented as a dot and MDS plots of all time steps are sorted and stacked along a vertical axis in the chronological order. All data points related to the currently focused egos are highlighted in red. And ego-networks of the same individual are connected with lines across time steps.

6.3 Summary Timeline View

We designed glyphs on a timeline to visually summarize the evolutionary process of an individual's ego-network. This design consists of two parts: a snapshot glyph indicating the network structure and properties at one time step, and a transition glyph representing the changes between two consecutive time steps. Based on the analytical questions (Q3 and Q4) in the mesoscopic level, we encoded several key variables about 1- and 2-degree alters in those glyphs. Thus, users can easily capture the main characteristics of a person's ego-network evolution. It also enables the comparison of multiple people's ego-networks using relatively small screen real estate.

Snapshot glyph. As shown in Fig. 4-a, the inner circle color represents the ego density which measures to what extent the alters connect to each other, where the darker purple means the higher density. The outer parts of the glyph indicate some information about the ego's 1-degree alters and 2-degree alters. First, a ring filled with four different colors shows the distribution of four types of 1-degree alters: 1) new alters who have no connection with the ego at the previous time step (green), 2) alters whose tie strength with the ego increases compared to that at the previous time step (red), 3) alters whose tie strength with the ego decreases (blue), and 4) alters who hold the same tie strength with the ego (light gray). The width of this circle is mapped to the number of 1-degree alters of the ego. Second, a gray ring is drawn to indicate the number of 2-degree alters with its width. However, it may be difficult to compare quantities of four types of alters in two glyphs. egoSlider also supports a bar chart based design as shown in Fig. 4-b. Similarly, the background square size is constant and its color represents the ego density. Four bars illustrate the numbers of different 1-degree alters. The top black bar indicates the 1-degree alter number and the bottom one shows the 2-degree alter number. Since it is easy to compare the total alter numbers in the pie chart design, and it is also visually attractive with a metaphor of an ego surrounded by alters, egoSlider uses this design as the default display. But users can switch to the bar chart based design on demand.

Snapshot glyph design alternatives. We considered several alternative solutions during our glyph design process. Line chart can also be used in the glyph but it has several drawbacks. First, the data

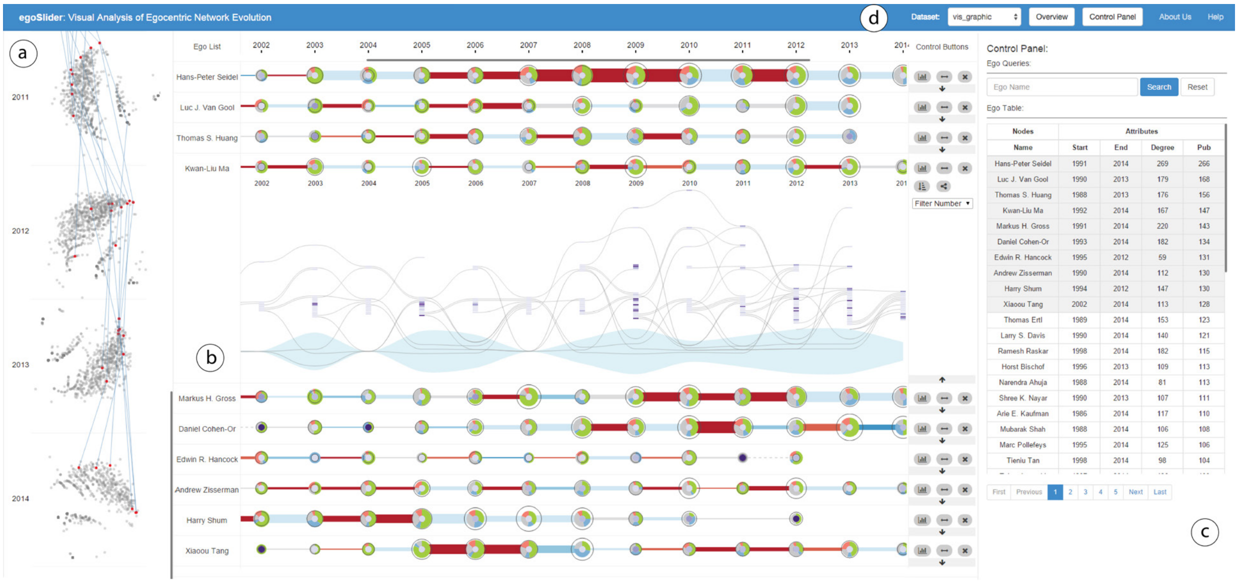

Fig. 3. The egoSlider interface consists of the following components: a) a Data Overview showing patterns of the entire dynamic ego-network data, b) a main canvas displaying detailed ego-network evolutionary history of selected individuals, c) a control panel with a search bar and a data table, and d) a toolbar for selecting datasets. Currently, the main canvas shows the Summary Timeline Views of the top 10 researchers in a DBLP collaboration network dataset based on their publication numbers, where Kwan-Liu Ma's timeline is expanded and shown in the Alter Timeline View.

presented in snapshot glyph has different natures and value ranges (e.g., ego density and alter numbers), so using a unified y-axis is confusing. Second, it might be difficult to track changes since the vertical space is limited. Third, line chart introduces occlusion for the transition glyph introduced later. Pie chart and bar chart do not have this visual clutter problem. Moreover, a number of alternatives pie chart designs have been experimented (Fig. 5-a). The first design choice uses the radius of a pie chart for the 1-degree alter number and the opacity of colors for the ego density. However, users can hardly see the alter type distribution when the 1-degree alter number is small. In addition, it is difficult to get an accurate value estimation on the opacity channel on many colors. The second design employs the inner and outer circle radii to encode the 1-degree and 2-degree alter numbers, and the diverging purple-yellow color of the inner circle to indicate which alter number is greater. Users may feel confused about this color-coding since the outer circle also employs a categorical color scheme. In the third design, the 1-degree and 2-degree alter numbers are encoded by the lengths of two vertical bars respectively. The colors of those bars represent the ego density. This design is limited when the vertical bars are short. Besides, the transition glyph may also affect users perceiving the length of the bars. For the bar chart based design, we also considered to use the size or height of the background square to indicate 1-degree alter number, but both designs make users difficult to perceive the ego density when the alter number is small.

Transition glyph. As Fig. 4 illustrates, we use the line thickness to represent the volume of consistent 1-degree alters between two consecutive time steps, i.e., those who remain directly connected to the ego. A diverging blue-red color scheme is used for the transition glyph to summarize the tie strength changes of those alters, which is in consistency with the color-coding of the snapshot glyph, i.e., red for a stronger change, blue for a weaker change, and light gray for no change. A dashed line is shown when there are no consistent 1-degree alters between the ego-networks at the two consecutive time steps.

Transition glyph design alternatives. Fig. 5 shows three design alternatives of the transition glyph that we experimented with, where different types of overall constant alters' tie strength changes are listed from top to bottom. In the first design, the line thickness encodes the 1-degree alter number and the tilting angle encodes the tie strength change. In this design, the tilt angle is somewhat restricted by the line thickness, so users may feel more difficult to discern different levels of tie strength when the line becomes thicker. We also explored the possibility to embed the gestaltline [20] in the second design choice. However, the gestaltline is not a common visualization encoding that

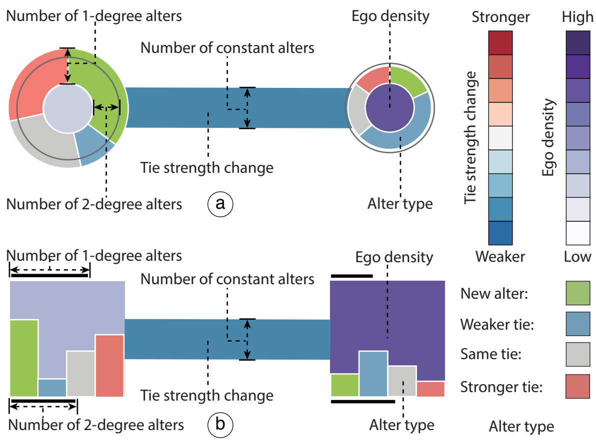

Fig. 4. The visual encodings of glyphs in the Summary Timeline View. The snapshot glyph represents an individual's ego-network structure and properties at each time step. Two design choices are shown: a) pie chart based, and b) bar chart based. The transition glyph summarizes the temporal changes between those time steps.

users are familiar with. Also, the tilt angle may also impact users perceiving the gestaltline thickness. In addition, we attempted to encode the tie strength changes of all three types of 1-degree alters, i.e., alters whose tie strengths are stronger, weaker, and the same across two time steps, by drawing three parallel lines. But we found that the transition glyph became too complicated and overwhelming, and those lower-level information can be accessed alternatively from the Alter Timeline View introduced below.

6.4 Alter Timeline View

The Alter Timeline View aims to support the microscopic level analysis (Q5-Q8) by providing detailed information of alters rather than overall statistics. The Summary Timeline View can only partially address Q5, whereas here users can track the temporal variations of tie strength between the ego and any individual alters as well as inter-alter connection structures. We considered node-link based and matrix based design choices before we adopted the current design, but they have the scalability problem as indicated in the literature (see Sec. 2 and [12]), whereas the line chart based design is more compact. As the direct-connected alters are more important, we use different visual aggregation methods to encode 1-degree and 2-degree

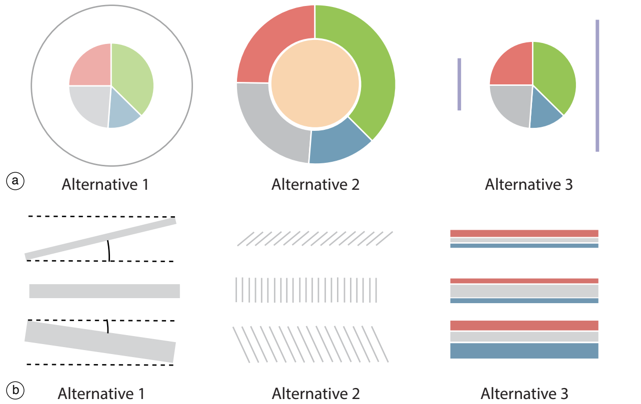

Fig. 5. Design alternatives of a) the default snapshot glyph and b) the transition glyph. For the transition glyphs, three different types of tie strength changes are indicated: increasing, constant, and decreasing (from top to bottom).

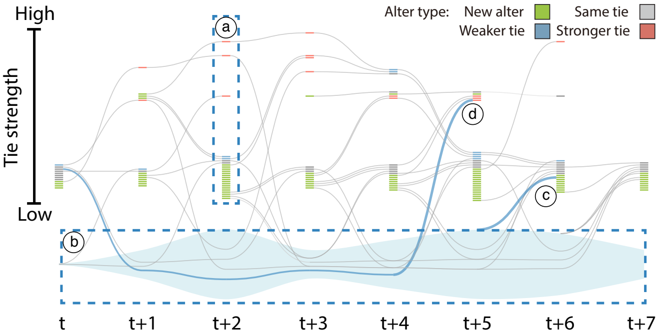

Fig. 6. The visual encodings of the Alter Timeline View: a) the 1-degree alter collections at one time step; b) the 2-degree alter volume flow, c) a new 1-degree alter who was the ego's 2-degree alter in the previous time step; and d) an alter transits to the ego's 2-degree neighbor and returns to the 1-degree neighbor after several time steps.

alters at different levels of scales (Fig. 6). In addition, two Alter Timeline Views can be displayed in one window together which makes comparison possible at this level.

Timeline encodings. As shown in Fig. 6, each 1-degree alter is represented by a small horizontal bar which uses the same color-coding schema as the snapshot glyph. Alter bars are organized vertically into groups based on their tie strength with the ego at each time step. From top to bottom, the tie strength between the ego and its alters decreases. We also support an interaction to group alters into connected components. In that case, the alters within a group belong to the same connected component rather than share the same tie strength. Note that the colors and positions of those alters are flexible in this visualization design. For example, we can use the color to encode alters' influence to the whole network, and group the alters into graph connected components vertically to help verify the "structural hole" theory [24]. As for 2-degree alters, which are less important, we aggregate them as a light blue flow chart shown at the bottom of this view to illustrate their temporal volume changes.

Same alters between consecutive time steps are linked by lines. Thus, each curve depicts an alter's tie strength evolutionary history along time. If an alter remains as the ego's 1-degree neighbor, we can simply draw a curve connecting them. To avoid edge crossing, we adopted an alter sorting algorithm. At each time step, all the alters are first sorted by the types of their tie strengh changes. Then, the constant alters are positioned in the same order as those in the previous time step. Finally, the positions of alters who become 2-degree alters in the next time step are lowered. In addition to the tie strength, the degree of an alter may change over time. For example, if an alter becomes the ego's 1-degree neighbor from its 2-degree neighbor in the network, a curve is drawn starting at the boundary of the 2-degree alter flow and ending at the alter bar at the next step (Fig. 6-c); similarly, if an alter changes from a 1-degree neighbor of the ego to a 2-degree neighbor, a curve is shown starting at the alter bar and connecting to the boundary of the flow chart at the next time step. In some situations, an alter may become 2-degree from 1-degree, stay as 2-degree for a while, and reappear as 1-degree, which is important to be captured in ego-network analysis. Thus, we encoded this alter behavior with a lurking curve in interior of the 2-degree alter flow to indicate such future reconnection. The position of the lurking curve is determined by the timespan while remaining as a 2-degree alter, where the longer the time interval, the closer the lurking curve to the bottom.

Design alternatives. We discussed several candidate designs of the Alter Timeline View before we made the final decision. One design choice is to position the lurking curves below the 2-degree alter flow separately (rather than on top of the flow and overlapped). This approach reduces the visual clutter when multiple lurking curves share a similar timespan, especially when the 2-degree alter number is small (making the flow tiny). However, it is not space efficient and much screen real estate is actually allocated to less important information. Another design choice is to encode 2-degree alters who changed to and from the ego's 1-degree neighbors with similar glyphs to Fig. 4 on top of the alter flow chart. However, we found those glyphs significantly occlude the lurking curves which represent alters constantly remaining as 2-degree neighbors. Therefore, we chose to draw curves connected to the flow boundaries to convey the same message, which is also consistent with the line-based visual encodings in this view.

6.5 User Interactions

To allow users to smoothly perform ego-network analysis from the three levels of scales and gain deeper insights, egoSlider incorporates a set of intuitive interactions to help users browse data through the multiple visualization views introduced above.

Navigating through multiple views. Users can glance at the entire dynamic ego-network dataset with the Data Overview to identify clusters and outliers. Alternatively, users can browse those egos through a table on the Control Panel showing the egos' names and some attributes. Once individuals of interest are identified, users can select them to compare their ego-network evolutional history with Summary Timeline Views on the main canvas. Further details-on-demand explorations can be achieved by clicking a button to expand the Summary Timeline View with the Alter Timeline View.

Filtering and searching. Users can interactively select an area of interest in the Data Overview, thus filtering out other egos and revealing how the similarities among those ego-networks evolve along time. In the Alter Timeline View, further filtering of alters based on their degrees is supported. Moreover, a search bar is provided for looking up a particular ego's name on the Control Panel.

Synchronizing and desynchronizing timeline. By default, all the timeline visualizations are synchronized globally along one time axis. Users can navigate through time using a global slider on the top. To compare two pieces of timelines from different time ranges, users can detach a timeline and shift it individually using a local slider.

Modifying alters' color-coding and/or positioning. Users can switch between different glyph designs (Fig. 4) in the Summary Timeline View. Users can also dynamically order the 1-degree alters in the Alter Timeline View based on different criteria, such as by tie strength, connected graph components, and other alter attributes. Similarly, the color-coding of alter bars is flexible to be changed to represent alter types, alter's overall influence, and so on.

Highlighting and brushing. Most of the visual elements in egoSlider are associated with informative tooltips, allowing users to have more information and learn about the visual encodings. Certain highlighting of visuals, such as alter evolutionary curves in the Alter Timeline View, can be fixed when selected. In addition, brushing & linking techniques are applied between different visualization objects. For example, hovering over an ego-network in the Data Overview reveals all other ego-networks sharing the same ego; hovering over an ego snapshot glyph or transition glyph in the Summary Timeline View indicates the corresponding alters in the Alter Timeline View; and hovering over an alter in the Alter Timeline View highlights its directly connected alters in the same ego-network.

Fig. 7. Partial visualization of the DBLP collaboration network dataset in the Data Overview: a) earlier years (1993–1999), and b) more recent years (2008–2014). c) Summary Timeline Views of the top 10 researchers based on their publication numbers; compared with Fig. 3-b which shows the recent years, it shows the early years of those authors.

7 Evaluation

Here we describe a usage scenario to demonstrate the effectiveness and usefulness of egoSlider using the DBLP collaboration network, and present a controlled user study to quantitatively compare the user performance of egoSlider with a baseline dynamic graph visualization.

7.1 Usage Scenario: DBLP Collaboration Network

Academic collaboration network, which is a specific kind of social networks, is a common dataset interested in many applications, because it is typical and has the challenges of being huge and dense. The ego-networks extracted from a large collaboration network indicate researchers' collaboration circles. The temporal evolution of a person's collaboration network can also reflect his or her career development. Do top researchers start to collaborate extensively in their early career time? Do they tend to keep any long-term collaborators? Many interesting questions can be asked. Our experts from the graph mining domain are particularly interested in this kind of data. Thus, we asked them to try egoSlider and conducted interviews with them. We derived the following usage scenario based on their observations.

From the DBLP dataset [1], we select 52038 papers from 31 conferences and journals in the fields of information visualization, computer graphics, computer vision, and human-computer interaction. We then identify 64892 authors and extract their ego-network evolutionary histories from 1975 to 2014. The tie strength between two authors are defined as the number of their collaborations in a year. We also define one's publication performance based on the publication number.

We first toggle the Data Overview to gain a big picture about the entire dataset. From the MDS plots which summarize all authors' ego-networks, we observe different clustering patterns along time. In recent years (2008–2014), there appears one giant cluster, a much smaller cluster, and several outliers (Fig. 7-b). As we move earlier, the sizes of different clusters tend to be more equalized, showing three or four groups where one is slightly larger (Fig. 7-a). This might indicate that nowadays most of the authors collaborate in a similar pattern (Q1). We then select the top 10 authors from the data table on the Control Panel based on their publication number. In recent years (2004–2014), we observe that their ego-networks (highlighted in red) are similar and distributed within a big cluster, but they are more spread out in earlier time (Q2). Another interesting fact we find is that Edwin Hancock's ego-networks are a slightly different (or far) from others in general.

To dive into more details, we leverage the Summary Timeline Views of those top 10 authors, as shown in Fig. 3-b and Fig. 7-c. We immediately identify that Hancock keeps a smaller group of collaborators compared with others, based on the sizes of snapshot glyphs and

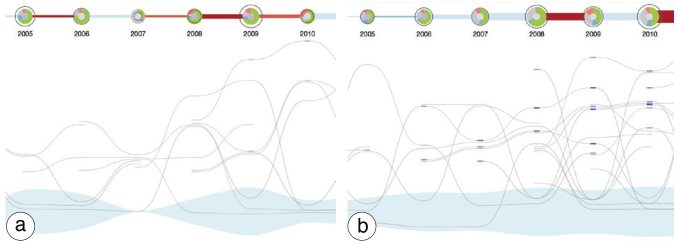

Fig. 8. Comparison of the Alter Timeline Views of a) Kwan-Liu Ma and b) Daniel Cohen-Or after filtering out their alters who collaborate with them less than 5 times. Alters are ordered by tie strength and colored by their publication performance (the darker the higher).

transition glyphs. Fig. 7-c indicates the early years of those authors' careers, where Xiaoou Tang's timeline is detached and shifted from the global time axis since his publication history starts from 2002. Most researchers' collaborator numbers are small except Xiaoou Tang in their early academic years. We can also see that many dashed transition glyphs exist, which may indicate some stage transitions. For example, Harry Shum received his PhD in 1996, Kwan-Liu Ma in 1993, and Daniel Cohen-Or changed his job between 1994 and 1996. As we further compare Ma and Cohen-Or's ego-networks along time, their 1-level ego-network sizes are similar but the 2-degree alter numbers are different, e.g., 2005–2010 in Fig. 3-b (Q4). Ma's 2-degree alter volume presents a periodic fluctuation pattern while Cohen-Or's is more stable, which can be better revealed after expanding their timelines into the Alter Timeline Views in Fig. 8 (Q3).

By using the colors of the alter bars to represent the publication performance, we notice that Ma's 2-degree alter volume increases as the number of his highly-performed 1-degree alters (Fig. 3-b where purple means higher performance). This may suggest that his 2-degree alters are strongly connected to those 1-degree alters, and other 1-degree alters have much fewer collaborators in general (Q5). Thus, we filter out all the 1-degree alters who collaborate with him less than 5 times, and find that their publication performance is not very high (Fig. 8-a). On the contrast, there still exist many highly-performed 1-degree alters in Cohen-Or's ego-networks after the same filtering (Fig. 8-b). This might be because that Cohen-Or works with many other professors whereas Ma usually collaborates with his own students (Q3 and Q4).

Further, in Fig. 3-b, by comparing the alter types over years, we find that more than 50% percent of Harry Shum's collaborators are constant alters in a consecutive sequence of years. His more stable collaboration relations may either be because he worked at an industry research lab where the employee turnover is less frequent than the student

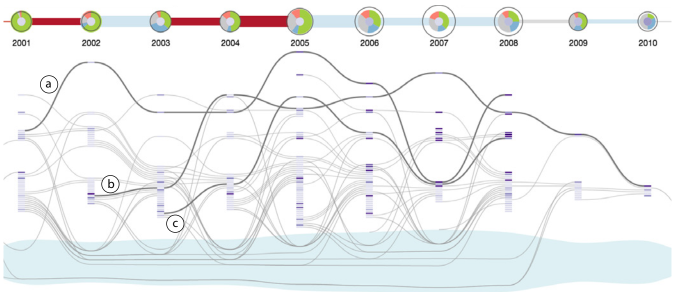

Fig. 9. Alter Timeline View of Harry Shum's ego-networks (2001–2010). Alters are ordered by tie strength and colored with publication performance (the darker the higher). Three long-term coauthors are highlighted: a) Baining Guo, b) Jian Sun, and c) Kun Zhou.

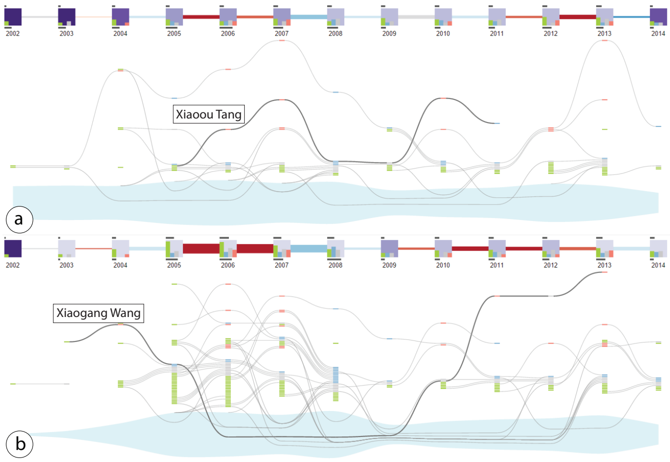

Fig. 10. Alter Timeline Views of a) Jian Sun and b) Xiaoou Tang, where alters are ordered by tie strength and colored with alter types. The highlighted alters are Xiaoou Tang and Xiaogang Wang respectively.

enrollment at universities, or because he worked at a leading position where he may have more stable colleagues (Q3). Moreover, Shum's egocentric network sizes expand significantly after 2004, which might be related to that the Managing Director position gave him a wider impact. After 4 years, his ego-network size has a big shrink, which could be because he was promoted as a Corporate Vice President and started to focus on Bing after 2007. He took the Executive Vice President position at Microsoft in 2013; and the visualization indicates that he has no further publications after 2012 (Q5).

To further explore Harry Shum's collaborators, we open his Alter Timeline View and group the alters into different connected components. As illustrated in Fig. 1-bc, his ego-network size increases and the alters tend to connect as a whole (Q7). We then want to identify who are the most constant collaborators of Shum, so we sort his alters based on the tie strength. Three long-term collaborators are revealed in Fig. 9 (Baining Guo, Jian Sun, and Kun Zhou). After mapping the color of the alter bars to publication performance, we observe that all the three collaborators did not publish many papers at the beginning and they become productive after leaving the collaborative relation. This suggests that they grew together in this process with Shum (Q6).

By hovering over those authors, which reveals their connected alters, we find that after 2008, Guo and Zhou continued for their collaboration while Sun had no connections with the other two authors (Q8). Does Sun have any constant collaboration with other established researchers? To answer this question, we thus display Sun's Alter Timeline View and filter out the authors who publish papers with Sun less than 10 times. The only other alter with good publication performance is Xiaoou Tang as shown in Fig. 10-a with the bar chart based design (Q6).

On the other hand, is Sun himself also Tang's most constant collaborator? We further display Tang's Alter Timeline View and apply the same filter. As shown in Fig. 10-b, apart from Jian Sun, there are actually other researchers who keep a more constant collaborative relation with Tang (Q8). For example, one of his students, Xiaogang Wang, re-collaborated with Tang in 2010 after leaving in 2006. This might be explained by that Wang went back to CUHK after his PhD study at MIT and worked as a colleague of Tang. Moreover, Tang's most constant 1-degree alters appear in 2005–2008, indicating more persistent collaborations (Q5). This might be because during that time, he worked as the director of the computer vision group at MSRA.

7.2 User Study

To quantitatively evaluate egoSlider's effectiveness, we conducted a controlled user study for comparing egoSlider with a baseline visualization. We focused on only evaluating the Summary Timeline View and Alter Timeline View in this comparative user study, because they are the main visual designs of egoSlider. We recruited 15 students (12 males) from a university with diverse majors, all with normal or corrected-to-normal vision and no color-blindness. Four of them had some knowledge of graph visualization. An online interactive system was built on a webserver (3.40GHz Intel Core i7 CPU and 32GB memory) for presenting tasks with different visualizations. Participants completed tasks on a client desktop machine (Intel Core i5 CPU, 8GB memory, and 1920×1080 pixel resolution) with the Chrome browser.

Comparison system. We chose the timeline-based approach with small multiples (Sec. 2.2) as our baseline for visualizing dynamic ego-networks, where the network at each time step was presented using the most widely-used node-link layout. The ego was shown in the center and the alters were placed around it. To adapt this baseline with ego-network analysis, we incorporated several interactions like brushing & linking. The node-link graph was also tailored to meet the requirements of various tasks by emphasizing the focused features. For example, we enlarged and highlighted the new alter nodes in all charts for new alter number comparison tasks, and encoded tie strength as the link width when appropriate. Visualizations of both egoSlider and the baseline in the experiment were interactive as described earlier.

Tasks and procedure. In light of the aforementioned analytical questions (Sec. 3), we developed 2 concrete user tasks for each mesoscopic level or microscopic level question, 12 in total (Table 1). We expected egoSlider to have better performance for all the tasks. We chose not to design tasks for macroscopic questions because they are related to the Data Overview (not focused in the study) and the baseline system is not scalable for such tasks (which results in enormous node-link diagrams). We also excluded the 2-degree related tasks because the baseline visualizations could become overwhelming due to the network sizes. A within-subject experimental design was used. Each participant performed 2 blocks $\times$ 12 tasks $\times$ 2 techniques $=$ 48 tasks in total. Within each block, the tasks were presented in the same order, and every task was shown in the two techniques (egoSlider and small multiples) one after another with different datasets. 4 predefined ego-network datasets were used and shuffled for each study. The order of techniques was counter-balanced in the whole experiment. A brief tutorial was given to help participants get familiar with our visual design and the experimental system before the study. In the end of the tutorial, a set of tests are used to confirm the users can understand and recognize our visual encodings including glyph size and color accurately. During the study, task description was presented first, and participants needed to click a start button to reveal the visualization and selected the answer from 5 choices. We recorded the response time and accuracy in the study.

Results. Table 2 summarizes the results from our experiment, where the better performance from the two techniques is highlighted (task time is highlighted if the difference is greater than 1s). On average, egoSlider outperforms the baseline in both accuracy (egoSlider: 92.5%, baseline: 83.6%) and time (egoSlider: 16.76s, baseline: 19.55s). The results indicate that egoSlider is more accurate in almost all tasks. The reason why egoSlider is less accurate in T9 could possibly be that users were confused about the alter bar position representing connected components just after performing the tie strength related tasks (T7 and T8). For task time, we first conducted overall analysis based on the level of tasks. Pairwise t-tests indicate that there were significant differences in task time for both

T1	How many egos whose 1-degree alter number keeps increasing?
T2	Which ego has the largest number of constant 1-degree alters at a time step?
T3	Which ego has the largest number of 1-degree alters at a time step?
T4	Which ego has the smallest percentage of new 1-degree alters at a time step?
T5	Which year does the ego has the largest number of 1-degree alters?
T6	How many years does the ego's 1-degree alter number increase?
T7	Which year does a specific alter have the strongest tie strength with the ego?
T8	How many years does a specific alter's tie strength with the ego increase?
T9	Which year does the ego-network have the largest connected component number?
T10	How many years does the ego-network's connected component number increase?
T11	Which year does the ego has the smallest percentage of new neighbors?
T12	How many years are the percentage of new neighbors of the ego less than 50%?

Table 1. Experimental tasks: T1-4 are mesoscopic level tasks, and T5-12 are microscopic level tasks.

Task	Task Accuracy		Task Time (s)		Task Time T-test
	egoSlider	Baseline	egoSlider	Baseline	$df = 29$
T1	**80%**	53.3%	**20.07** (6.74)	25.43 (10.15)	$-4.175, p < .001$
T2	**100%**	90.0%	**16.47** (8.69)	26.46 (15.38)	$-4.321, p < .001$
T3	**100%**	93.3%	17.58 (7.47)	**15.92** (6.04)	
T4	**90%**	63.3%	**17.77** (5.61)	25.18 (10.85)	$-3.571, p < .05$
T5	**100%**	90.0%	16.60 (4.75)	**15.19** (7.50)	
T6	**86.7%**	73.3%	**15.83** (4.33)	20.76 (9.59)	$-2.403, p < .05$
T7	100%	100%	**12.55** (4.08)	14.45 (4.12)	$-2.328, p < .05$
T8	**86.7%**	70.0%	16.75 (6.73)	16.48 (4.89)	
T9	86.7%	**96.7%**	17.64 (5.48)	17.15 (5.59)	
T10	**96.7%**	93.3%	**17.86** (6.15)	19.84 (7.20)	
T11	**91.7%**	86.7%	16.76 (7.28)	17.12 (7.49)	
T12	**96.7%**	93.3%	**15.29** (4.29)	19.63 (6.37)	$-3.139, p < .05$

Table 2. Experimental results and task time t-test results. Task time is shown in avg. (std.). T-values of significant differences are reported.

mesoscopic level tasks ($t_{119} = -5.5501, p < .05$) and microscopic level tasks ($t_{239} = -2.607, p < .05$). We then perform pairwise t-tests for each task, and significant differences were found in T1, T2, T4, T6, T7, and T12 (6 out of 12). The baseline was faster than egoSlider in T3 and T5, however, the differences were not significant. These tasks were both related to identifying the largest 1-degree alters, so it may be because the snapshot glyphs of egoSlider are too small. For T10, egoSlider was faster but not significant, however, the variance of the baseline was relatively high, indicating that the node-link visualization is not stable. Users need to manually change the alter bar position encoding in T9 and T10. This operation takes time and can cause confusion, which might be the reason that egoSlider had worse performance. As for participants' feedback, all of them thought egoSlider was more visually attractive, useful, and efficient than the baseline. Some mentioned that it took time to remember all the visual encodings while the tooltips helped a bit. One participant felt that it was not easy to scroll the timeline and suggested to widen the slider.

8 Discussion

The usage scenario and the quantitative user study demonstrate the effectiveness and usefulness of egoSlider. However, there still exist some limitations. First, there is a learning curve for using egoSlider. Although we intuitively encode important ego-network features in the Summary Timeline View and Alter Timeline View, users need to get familiar with the visual encodings before starting the exploration. Second, egoSlider encodes the alter bar position based on the tie strength of alters by default and the alter bars can be reordered in groups based on their connected components by clicking a button. Although this interaction enriches the system's functionality, users may be confused when switching between the two options, as indicated from the results of the user study. More distinct visual cues about those two view statuses are needed for improving the usability of egoSlider. Third, due to the limitation of MDS layout, two similar egos might be located at very different positions at two time steps, because the layout optimizes the similarities locally in each MDS plot. This introduces inconsistency in the Data Overview.

In addition, there are also many interesting perspectives that can be extended from the current egoSlider system. First, currently we only analyze the similarities of ego-networks within one time step. We can explore the temporal similarities by comparing the dynamic ego-network sequences of different egos across time. For example, users may want to analyze if two individuals share a similar evolutionary path. We can adopt time-series analyzing techniques such as dynamic time-warping [16] to identify such patterns. Second, other potential analytical methods can be incorporated to enhance egoSlider's abilities to explore larger dataset. For example, ranking of egos or other data mining algorithms can be used to help users start with exploring the most important people or anormalies in the data. Third, when users select too many individuals from the Data Overview, the connecting lines between the same ego across different time steps may become cluttered. This problem can be solved partially by applying edge bundling techniques [35]. Fourth, eye tracking devices can be exploited to further understand detailed user behaviors when exploring data with egoSlider.

A major consideration when designing egoSlider is scalability. From the algorithm perspective, egoSlider's data processing module takes several minutes to extract the ego-network structures from the raw DBLP records, compute the similarity metrics, and store them into MongoDB, which is acceptable as a one-off job. To minimize the initial page loading time, data is progressively sent from the server and rendered in the visualization client. From visualization perspective, in order to minimize user's memory burden, we only used 5 color hues in the visual encodings. Also, the snapshot glyph and transition glyph share the same color for alters of stronger/weaker ties (red and blue). Although users can scroll the visualization, approximately a maximum of 15 time-steps can be shown in one screen. Thus, visual aggregation of many time steps are needed to display really long timelines. In the current design, the number of alter bars we can support approximates the Dunbar's number (150) [26], i.e., the suggested cognitive limit number of people with whom one can maintain stable social relationships. Most of the top 10 researchers described in Sec. 7.1 have more than 100 alters in total, which is suitable in our current visualization. Though the alter numbers in online social networks might be much larger than the ones in traditional social networks [10], the scalability of the Alter Timeline View can be improved by aggregating the alter bars as rectangles and alter curves as flows. Finally, the current Alter Timeline View design may be cluttered in some extreme cases such as there are a lot of transitions between 1-degree alters and 2-degree alters while it can be solved by interactively filtering these edges.

9 Conclusion and Future Work

We have presented egoSlider, a visualization system for analyzing dynamic ego-network data, which incorporates a number of new visual encodings with three interactive visualization views to address ego-network analytical questions across different levels. A rich set of interactions is supported, allowing for flexible visual exploration through the three views. We have also described a comprehensive usage scenario with real dataset and a controlled study. The results indicate that egoSlider is effective in dynamic ego-network analysis and outperforms the baseline visualization in many analytical tasks.

In the future, we plan to embed some analytical methods to inspect the similarities between people's ego-network sequences along time and to detect trends and anomalies in ego-network evolution. We also want to incorporate multivariate visualization techniques to show more ego and alter attributes, as well as several extensions of the current system discussed in Sec. 8. Moreover, we aim to conduct more realistic case studies and user studies with a variety of ego-network datasets to further examine the effectiveness of egoSlider.

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