Dynamic Networks Analysis and Visualization through Spatiotemporal Link Segmentation

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Abstract—**Big network data analysis has become a challenging task not only due to increasing large volume but the appearance of dynamic spatial-temporal relationship. Both network topologies and their link properties are constantly changing as a result of newly established and torn connections. Traditional data mining techniques in large-scale dynamic networks are either incapable or computationally expensive. To that end, we developed a dynamic network analysis and visualization (DNAV) tool. One major component of DNAV is a dynamic graph in which links are divided according to their temporal dimensions. Each segment on network edges represents the dynamic network temporal evolution of graph properties, e.g., locations where the communications occur. Unlike animation approaches, the proposed static view of dynamic networks does not rely deeply on human cognitive ability on remembering changes over different time slots, thus dramatically simplifying the visual analytic process for dynamic networks. To further improve scalability of rendering large networks, data filtering modules such as time selection, hops settings, entities selection, and edge weight thresholds, are adopted in the visualization. Case study demonstrates the effectiveness of DNAV tool in understanding the dynamic network patterns and trends and the potential to analyze anomalies in dynamic communication networks.**

Keywords-dynamic network; spatiotemporal visualization; link segmentation

I. INTRODUCTION

As we move to big data era, the data is not only getting much bigger but more complex and dynamic as well. In facing with internet of things (IoT) and mobile social networks, as the number of nodes and their connection magnitude grow exponentially, their interactions are becoming more dynamic. Network connections can be established and torn down at any moment. The characteristics or properties of the network links can evolve with time. Examples of dynamic networks include wireless and mobile communication network, social network, IoT, sensor network, etc. Dynamic networks [1] are known for their temporally changing topology as a result of on/off patterns of network connectivity.

The challenges in analyzing dynamic networks lie in the constantly changing spatial-temporal properties and complex event interactions in large networks. While there have been data mining approaches [2] to analyze dynamic networks, the complexity is usually high to consider all possibilities for large networks. Visual analysis [3] of dynamic networks can be helpful sometime since patterns can be quickly examined by human therefore eliminating exhaustive search by data mining and machine learning process. Small multiples and animation are two typical visualization methods for dynamic network analysis, but it is difficult to track changes over time due to limitation of human cognition ability. While other visual methods such as multiple dimension visualizations [4]-[6] exist, there is generally a shortage of visualization readability and preservation of mental map [7]. As we transit to the world of big data, how to analyze large dynamic networks scalably and effectively remains a challenging research area.

Despite the challenges, we develop a relatively lightweight visual analytic tool that allows researchers and network operators to analyze patterns in their dynamic networks. Notably, some changes in dynamic networks are considered normal while other changes are not (i.e., anomalies). It is our intention to allow human investigators to understand the patterns/trends and detect those abnormal changes in highly dynamic networks. One major component of the Dynamic Network Analysis and Visualization (DNAV) tool is the dynamic graph view. The graph is a node-link diagram and we use it by taking advantage of people's familiarity with the graph. However, the dynamic graphs differ from traditional graphs in that a novel scheme is adopted to encode spatiotemporal information on the network connections themselves. The links in our dynamic graphs are divided into segments by their temporal dimension based on users' selection of edge properties. Each segment can be further divided if there are multiple status values within one time slot. Different colors are utilized to show dynamic edge property evolution over time. By dividing links into segments, we accomplish the goal of showing dynamic network in one single static view without requiring users to remember changes as in the animation schemes.

To improve our dynamic graphs' scalability, we have implemented multiple interactive functions, such as a time selection bar, which allows investigators to analyze the dynamic graphs only within certain time period. Another

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feature is the maximum hop setting, which enables analysts to choose how many hops from a selected node in the graph. The resulting smaller subgraphs allow scalable visualization of large networks. In addition, edge filtering by edge weights (e.g., number of connections) is included to address scalability issues. We evaluate the DNAV tool over publicly available datasets that contain over four million communication records. The proposed dynamic graph visualization effectively identifies the time and location of anomalous changes in network communication patterns.

II. Related Work

Understanding the dynamics of large complex networks has been a challenging yet important task. Traditionally, dynamic networks can be analyzed and visualized through animation. For example, GraphDiaries [8] tries to explore dynamic networks along three dimensions - time (when), graph elements (where) and type of change (what) - through interactive staged animated transition that highlights changes from one time step to another. However, animation approaches are limited by human cognition ability. Our approach seeks to analyze dynamic graphs in a static view thus is easier for users to preserve mental map.

Networks are commonly represented as node-link graphs. The underlying graph representation, i.e., adjacency matrix, however, can be used directly for analysis. The 3D matrix cubes [9] resulting from stacking adjacency matrix at each time slice are better for analyzing dense networks. In addition, Massive Sequence View (MSV) may be used to analyze temporal and structural aspects of dynamic networks. In this way, time ordering between node connections can be clearly viewed. However, as with any MSV, visual clutter can be a problem with large graphs. Circular MSV [3] may reduce clutter for better scalability.

Time-varying graphs can also be structured and visualized using the parallel edge splatting techniques and Rapid Serial Visualization Presentation (RSVP) [10]. The technique is a typical representation of juxtaposed visualization, in which, a dynamic graph is mapped on a sequence of parallel vertical lines with fixed vertical vertex positions in all of the graphs. Subgraphs between each two parallel vertical lines are used to represent one equal time period's data. While the method shows some usefulness in dynamic network analysis, it may have a high perceptual ability requirement for analysts to explore the whole network as there are so many subgraphs, and entities can be shown in the graph are also limited: too many vertexes on one vertical line will decrease the graph's readability.

For node-link graphs, research [11] shows that classic force-directed layout algorithm is suitable for time-varying graphs by using nodes and edges filter based on graph hierarchy. However, there exist other layout choices. For example, hyperbolic temporal layout method [12] was proposed to analyze large sparse temporal social network datasets. It uses topology-based-edge-clustering algorithms. Another example is TimeRadarTrees [13], [14], which use radial tree layout to draw the hierarchy, and utilizes circle sectors to represent the temporal dynamics of links in the graph. The layout has the benefit of reducing visual clutter comparing to node-link graph representation, but is not as easy as node-link graphs for people to understand as it does not have intuitional topological representation.

Large ego-centered networks can be divided into small graphs [15]. As general graph drawing techniques, different shapes, colors and filling may be used for rendering nodes and edges. 1.5D visualization design using temporal trend glyph for the focus node can be useful in analyzing egocentric dynamic network. 2.5D visualization or slice technique allows the analysis of both static snapshots of networks and their dynamics. Preserving mental map between consecutive timeslices is important. Multidimensional Scaling (MDS) [16] as a network layout method can be used for mental map preservation. Furthermore, Degree-of-interest (DoI) functions [17] can be defined to direct which areas need to be shown as global overview or at individual detailed level. Subgraphs' density can be encoded with node glyph.

Despite the above approaches, Dynamic Network Analysis (DNA) remains a hard research field. Such research is even more important and challenging when considering the unprecedented amount, complexity and dynamics of large network communication as we enter the big data era. This research looks at embedding spatiotemporal information into network links in dynamic communication network analysis and visualization.

III. Visual Analytic Design of Dynamic Communication Networks

Figure 1 illustrates an overview of the Dynamic Network Analysis and Visualization (DNAV) tool. The tool is designed to help investigators to understand and identify patterns from a dynamic communication network by iterative exploration. The main view is the dynamic graph based on node-link diagram to intuitively show the relationship among entities for communication networks. The dynamic graph view presents communication networks' dynamic topologies and properties over time in a static view. This is achieved through link segmentation with spatiotemporal property information, which is to be discussed in detail in following sections.

The dynamic graph view supports zoom and pan that allow detailed view and whole network view. The mouseover event on nodes will highlight a focus node and its surrounding neighbors with changing shape sizes and colors. The mouseover event on edges will show information about each individual link, i.e., the details of link property value changes over time. The color legend above the dynamic graph illustrates the color codes used and their meaning for easy lookup.

A. Dynamic Graph

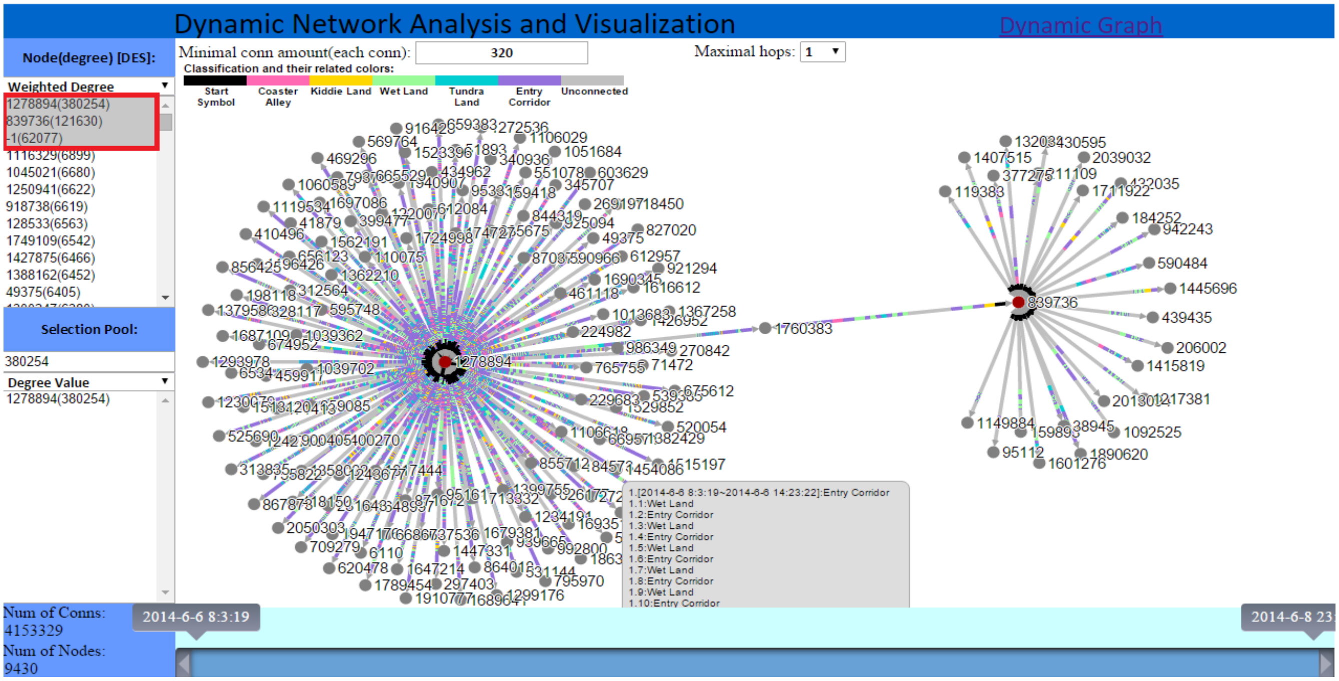
A dynamic communication network can be represented by a time-varying graph $G_T = < V_T, E_T >$, in which T represents the entire time period of analysis, V_T and E_T signify the network entity set and related communication set.

Due to the nature that most networks are large, we design four mechanisms to address scalability. The first mechanism is a time selection option through a double-end time slider bar (bottom of Figure 1), with which analysts can choose a customized time slice t from T to analyze dynamic graphs.

The second mechanism is a maximal hop selection (dropdown menu next to minimal connection text box) on top of the dynamic graph view. In our dynamic graph, each selected network entity v_i ($v_i \in v_t$) is regarded as root entity. Network entities which communicate with the root entity directly are considered to be within one hop of the root entity, and are referred as first hop entities. Similarly, entities which communicate with the first hop entities directly are within two hops of the root entity and so on. Once analysts set the hops value, the selected root entities along with entitles which are within the hops value of each root entity v_i, and their related communications will be added into graph $G_t = < V_t, E_t >$, in which t represents the selected time slice; V_t includes the selected root entities and entities which are within the selected hops value of each root entity; E_t signifies the related communication set of V_t.

The third mechanism is a node filtering by node weight (degrees) as illustrated in the node selection pool on the upper-left of the tool (see Figure 1). The nodes are sorted by their connectivity degrees (either weighted by considering connection magnitude or unweighted). Node degrees can be a relevant metric to measure the importance of nodes with which one may begin investigation. With the node selection pool, analysts can either type in one particular node ID or use mouse to select single or multiple nodes (entity set v_t ($v_t \in V_t$)) to analyze in the dynamic graph.

The fourth mechanism is to perform filtering based on edge weight as shown above the color legend in Figure 1. We add a minimal connection threshold input field for dynamic graphs. Once analysts input a minimal threshold value, we calculate the communication records that each merged communication e ($e \in E_t^m$) contains. Only merged communications whose communication records are more than the input minimal threshold value, along with their related entities will be added into $G_t^w = < V_t^w, E_t^w >$, in which E_t^w signifies merged communications whose communication records are more than the minimal threshold value and V_t^w includes the related entities.


Dynamic Network Analysis and Visualization

Dynamic Graph

Node(degree) [DES]:

Weighted Degree ▼

1278894(380254)
839736(121630)
-1(62077)
1116329(6899)
1045021(6680)
1250941(6622)
918738(6619)
128533(6563)
1749109(6542)
1427875(6466)
1388162(6452)
49375(6405)

Selection Pool:

380254

Degree Value ▼

1278894(380254)

Minimal conn amount(each conn): 320

Maximal hops: 1 ▼

Classification and their related colors:

Start Symbol	Coaster Alley	Kiddie Land	Wet Land	Tundra Land	Entry Corridor	Unconnected

1.[2014-6-6 8:3:19~2014-6-6 14:23:22]:Entry Corridor
1.1:Wet Land
1.2:Entry Corridor
1.3:Wet Land
1.4:Entry Corridor
1.5:Wet Land
1.6:Entry Corridor
1.7:Wet Land
1.8:Entry Corridor
1.9:Wet Land
1.10:Entry Corridor

Num of Conns: 4153329

Num of Nodes: 9430

2014-6-6 8:3:19

2014-6-8 23

Figure 1. Overview of the Dynamic Network Analysis and Visualization (DNAV) tool. Graph links are used to encode temporal dimension to analyze the spatial-temporal dynamics of network link properties.

B. *Link Segmentation Algorithm*

The dynamics in large communication networks not only reflect in their topology, i.e., entities may come and go and links may be created and torn down constantly, but also reflect in their communication properties P_{E_t} and dynamic changes of values for each property $P_{E_t i} \in P_{E_t}$. To show these two types of dynamics, we merge communication records (belong to E_t) with same entities but different timestamps, and divide the related link in a dynamic graph into k ($k > 1$) main segments, each main segment represents communication information in one sub time period $t', t' = t/(k-1)$.

Links in our design of dynamic graphs are divided into k time segments (Figure 2). Different colors are used to encode spatiotemporal information. For example, the first start time segment is denoted with black color. For the *k-1* segments, if communication disconnects during $(i-1) * t'$ $(2 \le i \le k)$, the i_{th} segment will be denoted with light gray color. Other customizable colors (except black and light gray) are used to show the dynamics of communications' property values, which also implicitly indicate that the related communications are connected during that time period.

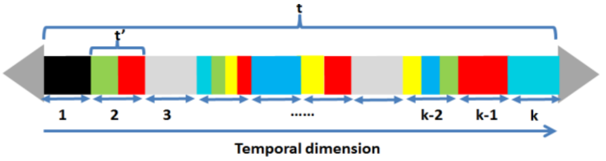


Figure 2. Dynamic graph links are used as a time dimensional axis and are divided into k segments, which may be further divided by multiple property values. Color coding: black (start time), light gray (no activity), others (link property values).

If two entities contact each other in the $(i-1)*t'$ $(2 \leq i \leq k)$ time period, and their communication property has only one value, then we will denote the i_{th} segment with one specific color (e.g., the $(k-1)_{th}$ and k_{th} segments in Figure 2. However, if during $(i-1)*t'$ time period a communication property has multiple values, we will further divide the i_{th} segment into subsegments by the number of property values. For example, as shown in Figure 2, when $i = 2$, the second segment is further divided into two subsegments denoted with different colors. Suppose the property chosen is the location, the two subsegments indicate that during this time slice, the communication has occurred at two different places. In our design, for simplicity and better visibility, the i_{th} segment will be equally divided into multiple subsegments no matter how many times each property value appears.

Algorithm 1 Link Division Algorithm

```
Input: $G_T = \langle V_T, E_T \rangle$ — a raw dynamic communication network, $k(k>1)$— $k$ main segments
Output: $G_t^{w'} = \langle V_t^{w'}, E_t^{w'} \rangle$
  procedure
    $G_t^w = \langle V_t^w, E_t^w \rangle (t_x \leqslant t \leqslant t_y) \leftarrow$ Data filtering()
    for each connectivity $e'$ in $E_t^w$ do
      for m $\leftarrow$ 2 to k do
        $e'$[m]['property values amount'] = 0
      end for
      for each communication record r in $e'$ do
        $t_i$ = r.connTime
        $p_i$ = r.propertyValue $\in [0, 1]$
        time_ratio = ($t_i$-$t_x$)/($t_y$-$t_x$)
        segment_ratio = time_ratio*(1-1/k)+1/k
        for f $\leftarrow$ 2 to k do
          if segment_ratio $\geq$ (f-1)/k and segment_ratio $<$ f/k then
            $e'$[f]['property values amount']++
            subsegment_sequence = $e'$[f]['property values amount'] -1
            $e'$[f][subsegment_sequence]['property value'] = $p_i$
          end if
        end for
      end for
      save information of $e'$ into $E_t^{w'}$
    end for
    return $G_t^{w'} = \langle V_t^{w'}, E_t^{w'} \rangle$
  end procedure
```

As discussed above, we now demonstrate the details of our link division algorithm (Algorithm 1). For $e' \in E_t^w$ $(t_x \leq t \leq t_y)$, we will iterate each of its communication records. Assume one of its communication records has a timestamp value of t_i we will first find out t_i's time_ratio (proportion of t) value by using the following equation:

$$time\_ratio = \frac{t_i - t_x}{t_y - t_x} \qquad (1)$$

As we have to keep the first main segment for start time notation, there will be only $(k-1)$ main segments on each link to show topology and property dynamics, so we need to normalize the time_ratio value into segment_ratio $(1/k \leq segment\_ratio \leq 1, [0,1/k)$ is kept for start time$)$. The normalization equation is shown as follows:

$$segment\_ratio = time\_ratio * \left(1 - \frac{1}{k}\right) + \frac{1}{k} \qquad (2)$$

Once we get the segment_ratio value for communication record with a timestamp of t_i, we will check which segment the communication record with t_i timestamp value belongs to, and calculate the number of property values that the related communication has in the segment by using binning method in data mining.

During $(i-1) * (t_y - t_x) / (k-1)$ $(2 \leq i \leq k)$ time period, if one communication link does not have any property value (i.e., the communication does not appear), the related link's i_{th} segment will be denoted with gray color. If one communication appears and has only one property value, the i_{th} main segment will be denoted with one specific color according to its property value. Otherwise if the communication has multiple property values during $(i-1) * (t_y - t_x)/(k-1)$, we will further divide the related link's i_{th} segment into subsegments according to how many property values that communication has during $(i-1) * (t_y - t_x)/(k-1)$. The dynamic graph after link division and color arrangement can be represented by $G_t^d = < V_t^d, E_t^d >$. One example of such dynamic graph is shown in Figure 3.

C. Implementations

We develop the DNAV tool based on the server-client model rather than a desktop application by taking advantage of scalability, accessibility and convenience. An investigator can analyze and visualize his network from anywhere in the world with the Internet and a web browser by visiting a URL.

As for data processing, given a communication network dataset, essential attributes are first extracted. Typically, the significant attributes that we will look for include timestamp, source ID, destination ID, and all relevant property information, e.g., location where the communication occurs, etc. The well-formatted data are stored in database server.

On the client side, the views are implemented using JavaScript with D3, JQuery and JQrangslides libraries. As users switch between views, move the time bar, or make filtering and selection, the operation will be transmitted under the AJAX mechanism to the server side asynchronously. On the server side, web service is set up to host user analytic requests from a client machine. When users interact with the DNAV tool in their web browser (e.g., select certain period of time or certain network entities), the request is sent back to the web server, on which the PHP processes query the database server and perform the dynamic graph construction, communication record merge, and link segmentation as discussed in the early sections. The results are then written to JSON files and sent back to the clients for their visual analysis in the dynamic graph view.

IV. Case Study

For preliminary results, we evaluate the DNAV tool over a large communication network dataset from Mini-Challenge 2 (MC2) of VAST 2015. The data is gathered at a theme park (DinoFun World) during 2014-06-06 to 2014-06-08 (Friday, Saturday and Sunday) to honor a famous soccer star (Scott Jones). However, a vandalism occurs sometime during the weekend. There is a need to analyze and understand the communication patterns in the park and when/where the vandalism occurs. MC2 data set contains 9,410 IDs (visitors or park services) and 4,153,329 communications. All visitors use a mobile application to check in rides and communicate with fellow visitors.

We extract the four attributes, i.e., time, from (sender ID), to (recipient ID), and location. Values for location can be Coaster Alley, Kiddle Land, Wet Land, Tundra Land and Entry Corridor. After loading the data into the DNAV tool, we find that the park was open around 8 AM and closed around 12 AM on each day. We move the time bar to select the whole investigation period (Friday - Sunday), and select "weighted degree" as the sorting option for entities. There are three IDs which stand out for their large volume of communications (highlighted with red rectangle in Figure 1), i.e., ID 1278894 (degree of 380254), ID 839736 (degree of 121630) and external IDs, denoted by -1 (degree of 62076). We choose these three IDs as starting points for analysis.

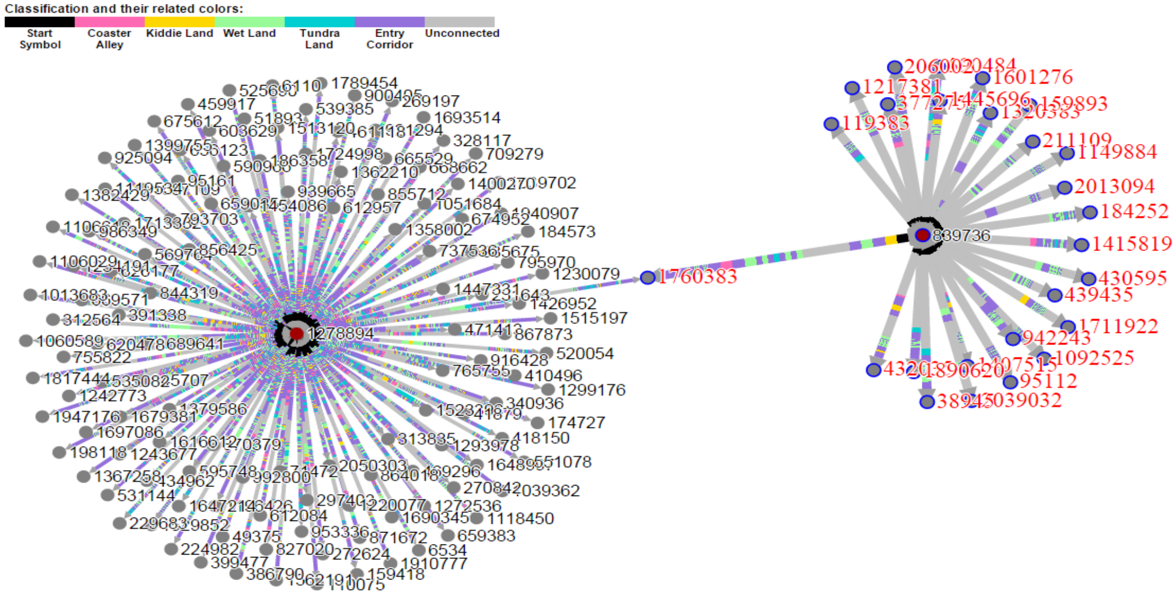


Figure 3. An example of dynamic graph visualization showing two top IDs communicating with others at different times at various locations.

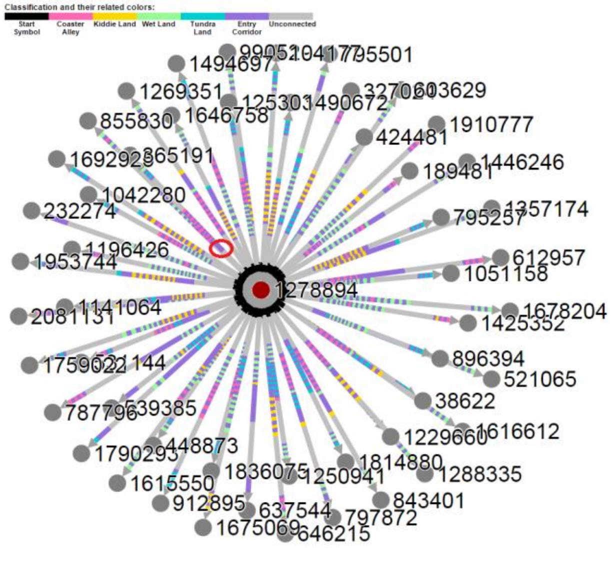
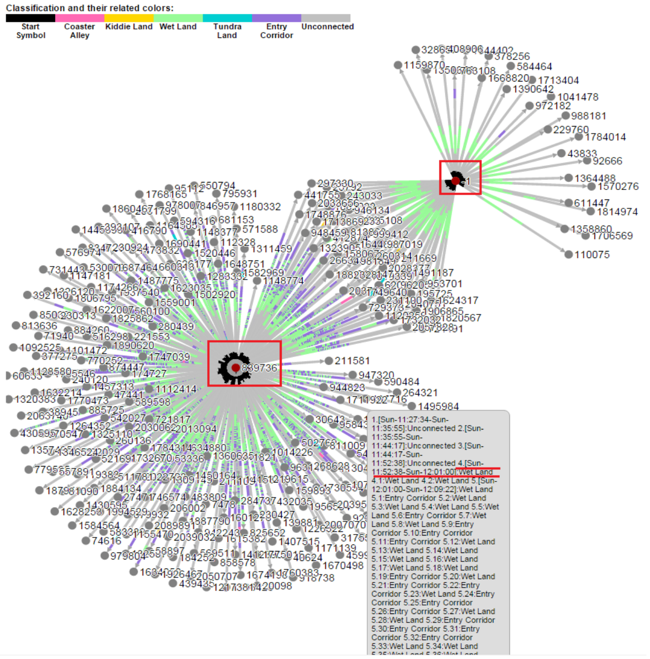


Figure 4. Communication patterns suggest ID 1278894 always starts at Entry Corridor (purple color) and bidirectional request-reply trend.

From Figures 3 and 4, communications of ID 1278894 always starts at Entry Corridor (purple color). This pattern implies that ID 1278894 is associated with park services, and visitors use the app to check into the park at Entry Corridor. Different from ID 1278894, ID 839736 communicates with other IDs at different locations but mostly ends at Entry Corridor. Similarly, its communication shows forward and back trend, i.e., other IDs always communicate with it first and it replies back. Based on these patterns, it is reasonable to assume ID 839736 may be one of other park services such as Information Desk in the theme park located at Entry Corridor.

The investigator moves the time bar to explore the dynamic graphs at different time slots. Figure 5 suggests that many IDs began frequently communicating with ID 839736 and external IDs (-1) at location Wet Land (green color) since 2014-06-08 11:52:38. Compared with Figure 3, neither ID 839736 nor external IDs exhibit similar communication pattern during other time periods. The investigator concludes that the vandalism was discovered in park around noon on 2014-06-08, when visitors began to frequently contact ID

839736, which may be the information desk in the park that visitors tend to consult with, and to contact external IDs that can be friends or family members that visitors inside of the park can communicate with when something special happens.



1.[Sun-11:27:34-Sun-11:35:55]:Unconnected 2.[Sun-11:35:55-Sun-11:44:17]:Unconnected 3.[Sun-11:44:17-Sun-11:52:38]:Unconnected 4.[Sun-11:52:38-Sun-12:01:00]:Wet Land 4.1:Wet Land 4.2:Wet Land 5.[Sun-12:01:00-Sun-12:09:22]:Wet Land 5.1:Entry Corridor 5.2:Wet Land 5.3:Wet Land 5.4:Wet Land 5.5:Wet Land 5.6:Entry Corridor 5.7:Wet Land 5.8:Wet Land 5.9:Entry Corridor 5.10:Entry Corridor 5.11:Entry Corridor 5.12:Wet Land 5.13:Wet Land 5.14:Wet Land 5.15:Wet Land 5.16:Wet Land 5.17:Wet Land 5.18:Wet Land 5.19:Entry Corridor 5.20:Wet Land 5.21:Entry Corridor 5.22:Entry Corridor 5.23:Wet Land 5.24:Entry Corridor 5.25:Entry Corridor 5.26:Entry Corridor 5.27:Wet Land 5.28:Wet Land 5.29:Entry Corridor 5.30:Entry Corridor 5.31:Entry Corridor 5.32:Entry Corridor 5.33:Wet Land 5.34:Wet Land

Figure 5. Shift of communications patterns of two IDs (839736 and external) with one-hop filter between 2014-06-08 11:27:34 and 2014-06-08 12:51:10. IDs start to frequently communicate with 839736 and external at Wet Land (green color) where the vandalism happens.

V. Conclusion

With the rapid growth of interconnected devices and information exchanged in the big data era, many networks such as social, mobile devices, sensors, etc., are not only much larger but also more complex and dynamic. How to effectively analyze and understand these dynamic networks becomes an important yet challenging research topic. This work develops algorithms to represent spatiotemporal communication patterns for dynamic networks by exploring links as temporal dimensions. The encoding scheme in link segmentation design allows efficient analysis of pattern evolution of generic properties in one static view. A visual analytic tool is developed to demonstrate the usefulness of the proposed analytic method.

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