VISUAL ANALYTICS OF MOBILITY NETWORK CHANGES OBSERVED USING MOBILE PHONE DATA DURING COVID-19 PANDEMIC

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Abstract

The limited exchange between human communities is a key factor in preventing the spread of COVID-19. This paper introduces a digital framework that combines an integration of real mobility data at the country scale with a series of modeling techniques and visual capabilities that highlight mobility patterns before and during the pandemic. The findings not only significantly exhibit mobility trends and different degrees of similarities at regional and local levels but also provide potential insight into the emergence of a pandemic on human behavior patterns and their likely socio-economic impacts.

Keywords— COVID-19, graphs, mobility patterns, flow map, visualization

INTRODUCTION

Population mobility, i.e, the movement of individuals across geographic space, is an essential factor determining the course of a pandemic disease spread. Specifically, after a surge in the COVID-19 pandemic at the beginning of March 2020, the governments imposed a widespread lockdown, asking their citizens to reduce their mobility and social contacts. Evidence shows that reducing crowd-mobility had a real impact on the control of infection rates [1]. For instance, it has been predicted that the Chicago metro area would have seen six times as many infections by the beginning of May if people had not limited their mobility in March [2]. Studying the impact of lock-down policies not only is of major importance for epidemiologic and health studies, but it is also a major research question for socio-economical and human behavior studies, as clearly the pandemic has generated major changes at all levels of scale worldwide [3, 4].

In the era of big data and in the age of the digital revolution, the increasing pervasiveness of location-aware devices such as mobile phones and real-time sensors as well as large information infrastructures, large amounts of human movement data are readily available. This offers many opportunities for the research community to analyze the trends, changes, and territorial impacts that appear at different national, regional, and local scales. Such large mobility flows materialize geospatial network graphs that denote the interactions between the underlying regions and cities where they occur. These geospatial networks can be represented at different levels of scales, where nodes represent either regions or cities, and links denote movement flows and transportation patterns between them. Additionally, these graphs can be complemented by additional semantic data to complement and enrich the model for further management and analysis.

Over the past few years, several modeling and analytical solutions have been developed for the analysis of the complexity of trajectories and mobility flows as derived from large sensor-based and social media data infrastructures [5]. Most of them combine computational, geographical, and network theoretical principles and have been developed over a large diversity of approaches. One can make a difference between data-oriented and structural approaches. Conventional data-oriented efforts first rely on sound data models complemented by data manipulation and analytics (clustering, data mining, deep learning) where the objective is to extract movement patterns in space and time [6]. Structural approaches, per definition, rather rely on the representation of the underlying networks that emerge from mobility and transportation flows, thus offering a network representation, in which graph principles and analytics might be applied [7, 8]. The main advantage of these structural oriented models is that, by modeling crowd-movement over the underlying structure of a graph, one can characterize the architecture and dynamics of human mobilities over the represented network based on the strengths of interaction links between the underlying nodes using measures ranging from simple counting to construction of origin-destination (OD) flow matrix and analyzing it based on the criteria such as centrality, connectedness, path cost length, degree, and clustering index.

Indeed, while network and graph-based measures are applied at either global or local levels, and potentially at different scales and over time, a sound understanding of the trends and flows that emerge surely requires the development of appropriate and comprehensive visualization and exploration techniques. Two main approaches have been mainly developed for the visual analysis of population movements: matrices and flow maps. A common one is based on Origin-Destination matrices but this fully quantitative approach does not fully embed the geographical dimension and even the temporal one. On the other hand, a flow map shows movement trends, with flows represented by straight or curved lines. However, such maps quickly become illegible as data size increases, with severe cluttering problems caused by massive intersections and overlapping of flow lines. Several approaches have been so far proposed to address this problem for flow mapping, each of which has specific strengths and weaknesses [9].

To address the above limitations, the research presented in this paper combines a series of visual approaches, from network to geographical flow data analysis, and where structural and data-oriented representations together show how complex geospatial network data is extracted from mobility data can be converted into meaningful information using a proper network and GIS-based visual approach. The aim is to gain a better understanding, and knowledge of, complex movement networks through a visual analytics approach to information generation. The whole approach is applied to a large set of experimental telecommunication data that covers the pre-pandemic and COVID-19 outbreak.

The rest of the paper is structured as follows. The next section presents the problem statement, while the following section briefly reviews related work. The next section presents the methodology and reports on the findings. Finally, a conclusion summarizes the paper and draws a few perspectives for further work.

PROBLEM STATEMENT

In response to the COVID-19 outbreak, measuring the impact of social distancing regulations on movement patterns, and subsequently on the spread of COVID-19, is still a critical challenge for policymakers and health authorities. Therefore, IT companies and mobile phone operators have been extremely active in developing contact-tracing applications that could reduce the spread of the virus [10]. Moreover, aggregated location data derived from mobile phones and large movement flows provide valuable trajectory data that can be very useful for analyzing patterns of change in the way humans behave before and during the pandemic surge.

In our previous work [11], a study was conducted on anonymized data of approximately 1.2 million mobile handsets which were provided by a large Austrian internet service provider (ISP), comparing human behavior before, during, and after lock-down measures. The movement of the population is quantified by several measures ranging from simple counting to estimation of the mobility via ROG (radius of gyration) and activity space, to the evaluation of OD-flow matrix in different time periods and at a multitude of spatial resolutions such as federal states, political areas, and municipalities. Overall, the findings derived from a combination of statistical, geometric, and graph-based analytics showed COVID-19 restrictions led to a dramatic reduction in human mobility in the whole country.

However, and so far, the large extent of the movement patterns that appear were mostly presented using either statistical or basic maps that did not fully encompass the respective impact of the mobility patterns and changes that appear at different levels of scale and temporal granularity. This leads us to consider in the present work exploratory data visualization methods that can be defined as a flexible and interactive graphical representation of data, and where the objective is to provide a better understanding of the data and patterns that appear [12]. During the COVID-19 outbreak, geo-visualization has been largely exploited to present the numbers of the COVID-19 pandemic diffusion at different scales, to understand and anticipate the pandemic impact [13]. Despite the interest of many of the current interfaces developed so far, there is still a need to develop interactive and intuitive interfaces that will combine the complementary dimensions that play a role in the spread and impact of the COVID-19 pandemic.

A common popular approach of geo-visualization when applied to the analysis of movement patterns is flow maps [9], which represent movements as lines connecting pairs of locations on a geographic map and their magnitudes by varying the widths or the color intensities of the lines. Whilst flow maps are intuitive, they perform well when applied to relatively small data sets. Since pandemic-related movement data sets are often very large, involving millions of people and locations, their flow map visualizations quickly become cluttered and difficult to read. Furthermore, the complex nature of such data makes it difficult to find a suitable representation showing how spatial relationships change over time at different levels of scale. The wise integration of the time component to the movement representation is another challenge. Overall, though numerous techniques exist to offer solutions to the inherent complexity in geospatial networks, it is still a challenging problem to analyze massive spatial movement data, discover useful patterns, and facilitate the pandemic decision-making process using flow maps.

The goal of this research is to investigate the existing methods which can deal with data of such a large volume and complexity and discover interesting patterns which can help decision-makers understand how humans move or a pandemic spread across space and time.

RELATED WORK

At an unprecedented scale and speed after the emergence of COVID-19, many experimental research and studies based on real-time positioning data have been oriented to the impact of either lockdown and distancing rules on the propagation of the virus [14, 15] or confinement measures to human social and mobility behaviors [3, 16, 17].

These studies show how restricting measures changed the daily lives of people – their spatial behavior and social interactions. In an intra-urban scale, say Rome, the number of people moving within the city dropped by over 80% in the lock-down time slot compared to before [18] and after the easing of the restrictions, the mobility of people and their social interactions have recovered to some extent [19]. Also, from the country-wide perspective, as in Italy [20], the structure of mobility flows of people changed as flows between regions within a country decreased. Similar patterns emerge from a global perspective as daily mobility in 36 selected countries on several continents shows similar trends of reduction of mobilities, with some exceptions [21].

A peculiarity of most if not all these studies is that they widely involve close collaboration between epidemiologists, computer scientists, and telecom companies using anonymized, aggregated data sets along with analytic support and interfaces for interpretation, early warnings, and development of counter-measures [22]. A key issue most of these initiatives have to deal with was the urgency of the infrastructures and analytics to deploy, which generates high pressure on the functional and human levels, the need for data protection and integrity measures, and indeed the overall quality of the predictions made. Moreover, the need for tangible and comprehensive outputs requires sought documentation and user-oriented interfaces to communicate with health experts, decision-makers, and the large public. Indeed, the range of opportunities to examine and study such mobility data at large scales is very large, and so is the sort of questions and metrics one might examine.

Visualization is an essential tool for the investigation of mobility flows between geographic locations. Visual displays allow analysts to look at the data from different perspectives and fulfill diverse analytical tasks. Different surveys of the state of the art in visual analytics concerning the analysis of movement data are conducted [9]. Traditional flow visualizations usually fail due to massive clutter and limited support for investigating the complex variation of the movements over different time periods. However, a wide variety of methods and tools for the analysis of movement data have been developed in recent years. For instance, FlowMapper.org was developed as a web-based framework for the automated production and design of origin-destination flow maps [23]. Also, visual models and analytics have been progressively implemented to favor the development of a more comprehensive understanding of mobility patterns and changes that arise during the time of the pandemic [24, 25]. For instance, hot spots and heat maps have been produced for deriving COVID-19 exposure risks in Singapore [26]. Flow maps and temporal evolutions have highlighted the range of interactions that appear between the evolution of the COVID-19 pandemic and mobility patterns between regions in Spain [13]. Though the structure of underlying changes in mobility and social distancing is examined in such studies, it is argued that they might not describe all aspects of mobility perfectly.

METHODOLOGY AND RESULTS

This study looks into the impact of the recent COVID-19 epidemic on the daily mobility of people in Austria using large-scale anonymized and aggregated mobile phone location big data. To Understand the change in mobility patterns during the Covid19 Pandemic, three time phases including (I) Pre-lock-down: before 15th of March, (II) Lock-down: 15th of March until 2nd of May, and (III) Easing: 2nd of May onwards are considered.

Telecommunication operators have made available a wide range of spatio-temporal data sources that can be used as informants of human trajectories and activities. For the purpose of human sensing, Call Detail Records (CDRs) as a mobile operator-based data source includes information about all interactions between a mobile phone network and mobile devices containing anonymized user information relating to people in connection with the network operators, the nature of the communication activity (voice, SMS, data, etc.), duration of the activity, starting time of the activity and servicing cell identification numbers of both the sender and the receiver. Each cell-id of the network topology and CDRs are an attractive source of location information for three main reasons:

1. They are collected for all active cellular phones, which number in hundreds of millions of records;
2. They are already being collected to operate the networks so that additional uses incur little marginal cost; and
3. They are continuously collected, thus enabling timely analysis.

CDRs data that is utilized in this study were recorded and anonymized with a rotating key. Then, they are localized with a (xlong; ylat) using the collective cell towers data. As a next step, each individual's stays were detected by spatio-temporal clustering with a stay duration of at least ten minutes and their enrichment with regional data such as federal states or a political area by spatial-join. Finally, the origin-destination (OD) matrix was created by daily aggregating all the devices by counting the individuals moving from one spatial unit to the other. The details of this data processing pipeline is provided in [11].

From this relatively large set of movement data, the objective is to develop a series of data analysis and visual exploration tools that might provide a better understanding of the mobility patterns and changes that appear after the emergence of the COVID-19 outbreak. The aim is to analyze such patterns at different levels of scale in space, and time, and to observe throughout the whole Austrian country regular trends and possible outliers. Moreover, a specific objective of our research is to develop multi-scale exploratory visualizations that combine the semantic, spatial, and temporal dimensions.

A series of analyses were conducted using JFlowMap [27], a network visualization tool, FlowmapBlue [28], the in-browser version of JFlowMap, and Flowstrates [29], a graphical tool for the exploration of spatial interactions development in time, with two goals in mind: (1) To effectively represent flow maps with large numbers of flows; and (2) To facilitate the exploration of temporal changes.

The basic view provided by the JFlowMap is a flow map whose mobility flowing between geographical locations are shown by straight lines and their directions by color markers. Flow quantities are mapped to two visual variables: the widths and color saturations of the flow lines. The "small multiples" display is one of the most often used techniques for representing movement data over time. It uses multiple charts laid side-by-side, corresponding to consecutive time periods [30]. Fig. 1 presents the "small multiples" view of crowd-mobility through Vienna over three time periods including pre-lockdown, lockdown, and easing. What is immediately apparent when looking at Fig. 1 is which parts of this state have more in- or out-flows (most of the movements have taken place in central regions). Also, the dramatic reduction of mobilities in the lock-down time period and its increase again in the easing period is evident. Another interesting trend is that the overall structure of the network of migration flow has not changed.

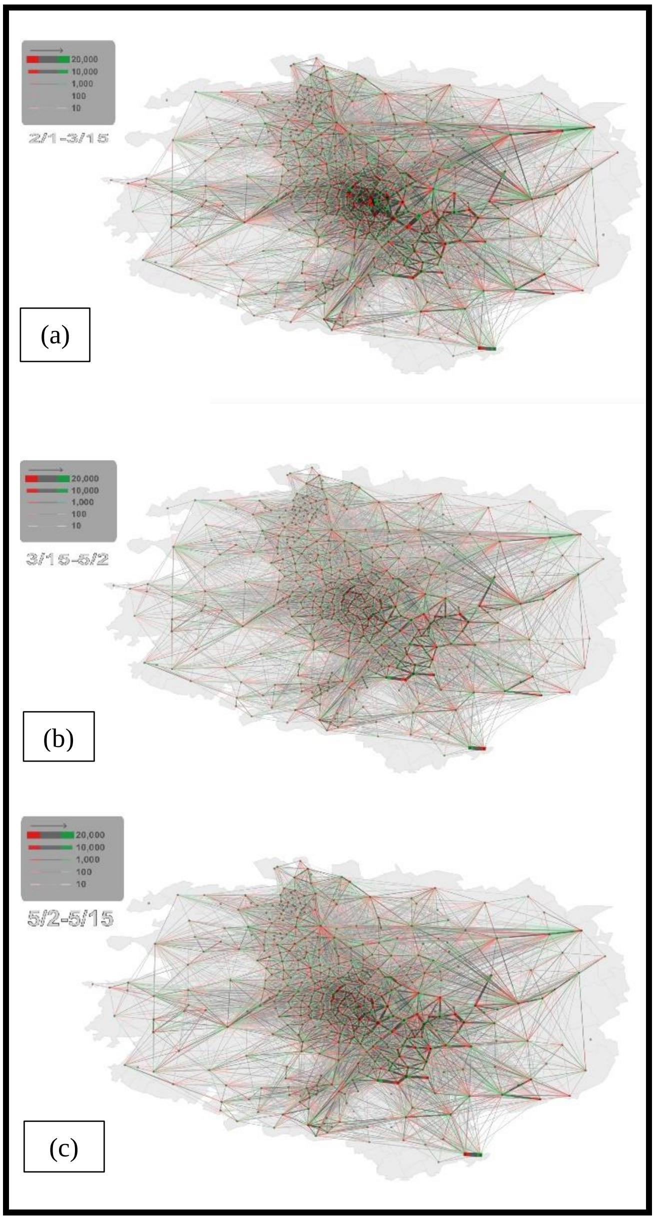

Figure 1. A visual presentation of the mobility flow network in Vienna during (a) pre-lockdown (b) Lockdown (c) Easing time periods.

In order to reduce the number of displayed flows, and thus minimizing line intersections and the occlusion of the flows, nodes are clustered using a hierarchical clustering algorithm with a distance metric: After obtaining the clusters, the nodes inside each cluster can be merged so that only aggregated flows between the merged nodes are displayed in the cluster centroids and as a result, the number of nodes, flows and the cluttering are reduced [31]. Fig. 2 shows the crowd-mobility flows through Vienna state as a clustered view. The readability of flow maps has been improved as the information in the individual maps is presented in a summarized way, which makes high-level patterns as well as the patterns that can show some local impacts more apparent.

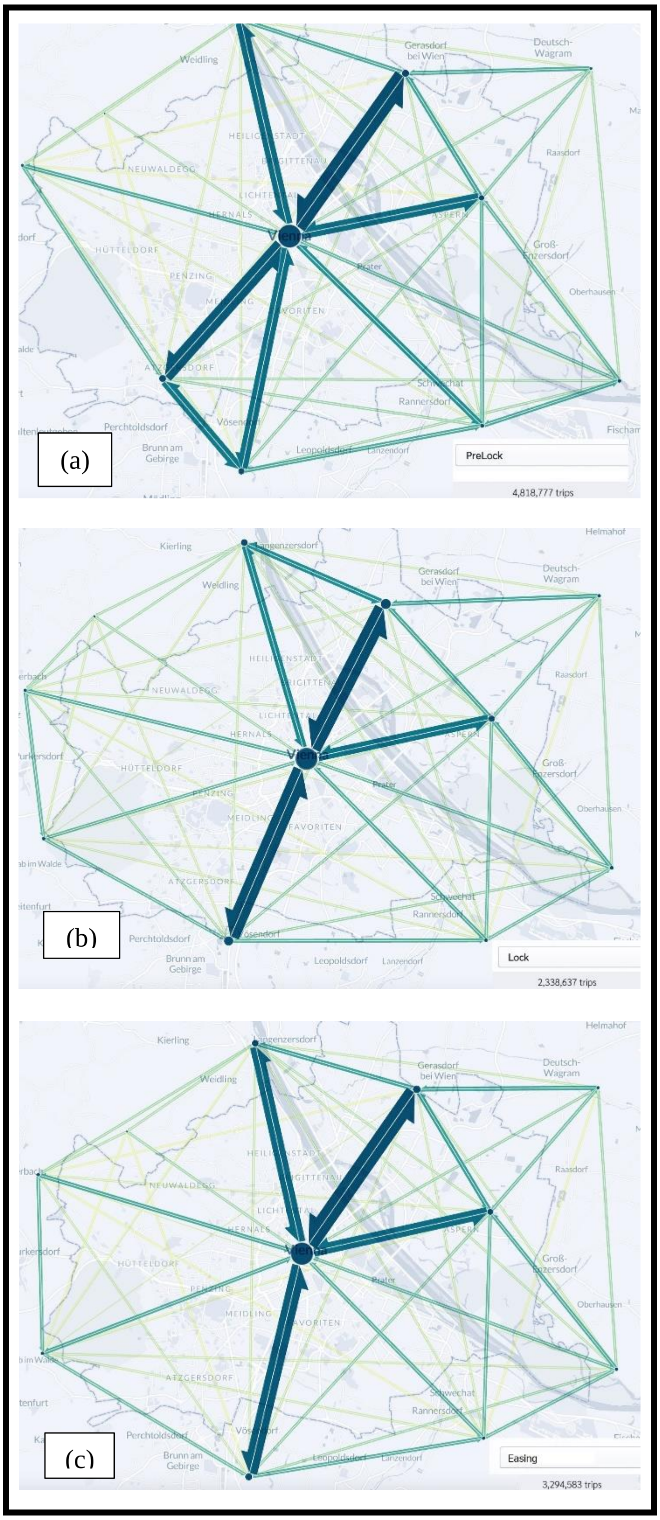

Figure 2. a clustered version of the mobility flow network in Vienna during (a) pre-lockdown (b) Lockdown (c) Easing time periods.

The above figure visualizes a big picture of Vienna's crowd-mobility. It is observed that the overall structure of movement remained consistent over time, except for some changes in the southern part of this state. In continuation, Fig. 3 illustrates how this technique is applied to visualize crowd-mobility in a higher level of spatial resolution across the whole country of Austria in two time slots as pre-lockdown and lockdown.

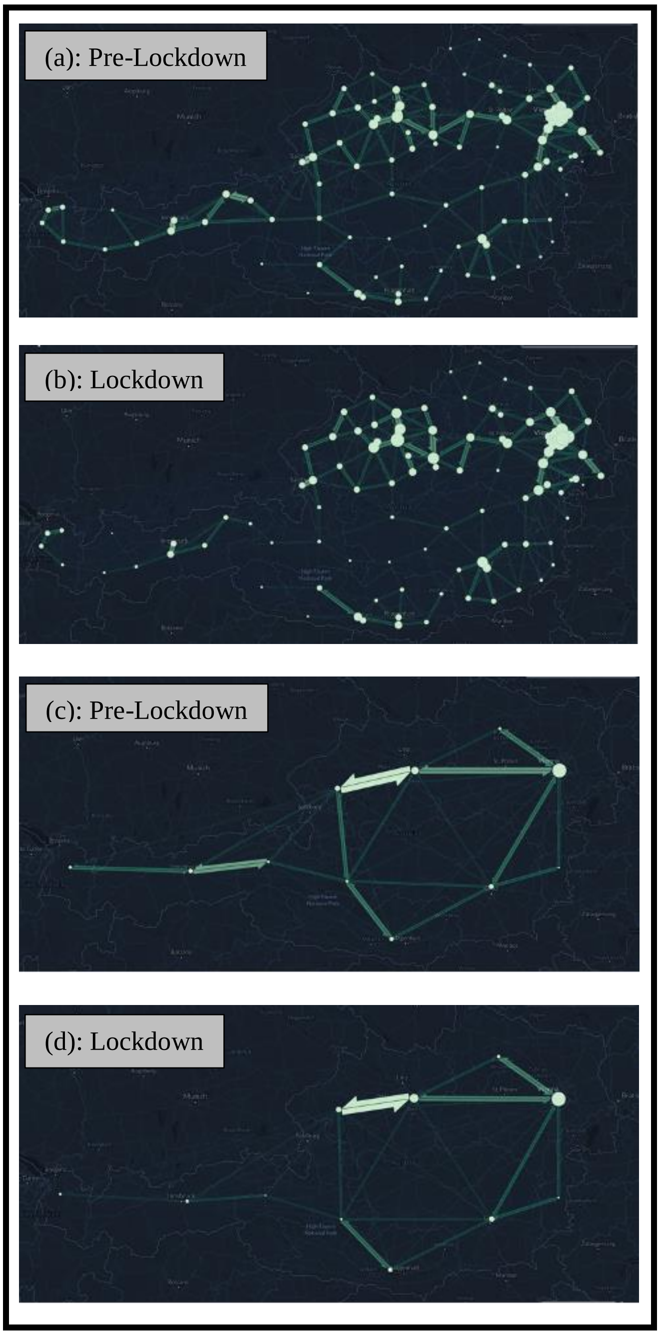

Figure 3. Mobility flows between political areas across Austria country before and during lockdown measures: (a-b) non-clustered (c-d) clustered version.

Figures 3.a and 3.b illustrate that the reduction of movements between administrative areas is consistent throughout Austria. On the other hand, the clustered version of maps (Figures 3.c and 3.d) show that the western regions (i.e. Tyrol, Vorarlberg, and Salzburg states), where the first positive COVID-19 cases were reported, have the highest reduction rates during the restriction periods. This finding supports the reported results in [11] that stated subdivision of communities into smaller ones (because of the strengthening of local interactions and reduction of movement to faraway places) has generally occurred in the western political area of Austria. Finally, the visualized movement patterns illustrate the continuity of changes: The change from A-to-B and B-to-C has a significant degree of consistency (i.e., the changes are not sudden).

Another technique that can help to make a cluttered graph visualization more readable is flow bundling. JFlowMap has an implementation of the Force-Directed Edge Bundling (FDEB) algorithm proposed by Holten [32]. This algorithm runs a step-by-step simulation of a process in which flows that are close to each other and have similar orientations attract each other. As a result of the process, the shape of the flows is changed by forces attracting the flows to each other and the flows are visually rerouted along their joint paths so that they form bundles emphasizing the high-level graph structure and revealing some patterns, like the highly connected regions. A bundled version of the interstate crowd-mobility across Austria for the two pre-lockdown and lockdown time periods is presented in Fig. 4. On these figures the major changes in the structure of movement flows clearly appear since a bundled flow map gives a better overview than a straight-line representation.

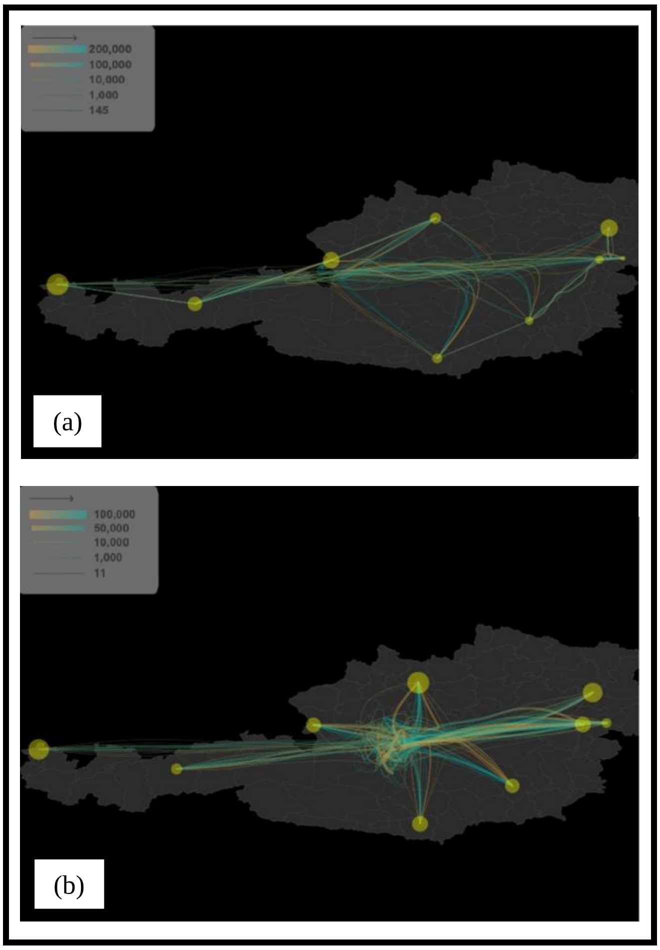

Figure 4. Bundled mobility graph in (a) Pre-lockdown and (b) Lockdown time periods.

The small multiples display allows us to see the changes over time for a few numbers of time periods by putting separate flow maps next to each other. However, this solution is not scalable. Why so, for instance, if the time periods would be defined as daily or weekly ranges, the individual maps must be smaller, and so it will be more difficult to see the details. To address this issue, we utilized the Flowstrates [29] to resolve the challenge of how to bring together the spatial and temporal dimensions of crowd-mobility data. In this visualization approach, the origins and the destinations of the flows are displayed in two separate maps, and the changes over time of the flow magnitudes are represented in a separate heatmap view in the middle in which the columns represent time periods. Fig. 5 is the result of applying the Flowstrates approach and depicts a dramatic reduction of movement over a specific time period, which is the effect of the lock-down measures.

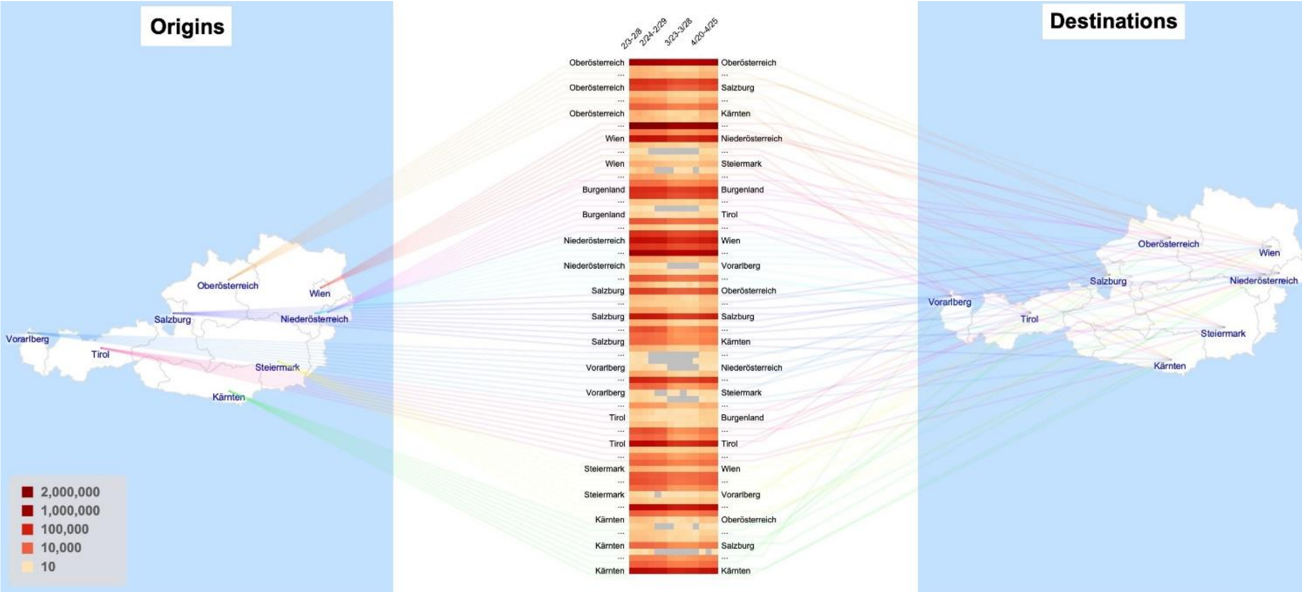

Figure 5: Presentation of changes in the magnitudes of inter-state mobility flows over time.

Making the visualization more comprehensible, the flows represented in the heatmap can be aggregated, by their origins (Fig.6.a) or by destinations (Fig 6.b) so that each heatmap row represents the total magnitudes of the outgoing/ingoing flows of each of the origin or destination.

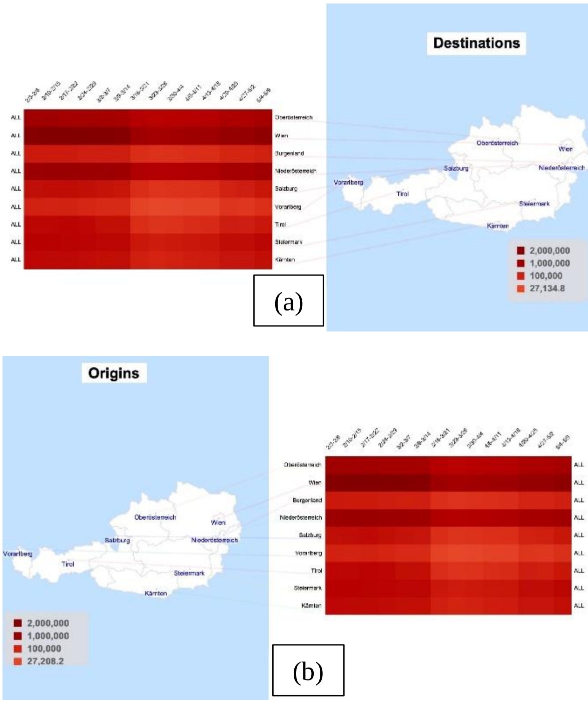

Figure 6. Flow aggregation: (a) The incoming flows totals for the Austrian states (b) The totals of the magnitudes of the flows originated in each state.

Moreover, we can choose a location or a region in the origins map, then find out what is going on in the heatmap or in the destinations map. This is conducted for Tirol and Salzburg states as an instance and shown in Fig 7.

Finally, this analytical approach allows us to visually investigate possible relations between movement patterns and the location (i.e., if close regions have the same movement pattern and the same changing pattern), which cannot be simply accomplished through pure statistical analysis.

CONCLUSION

This paper deployed a series of visualization techniques to identify not only the changes that occurred in movement patterns during the pandemic, but also to highlight how the changes might be related to location. It was only an example of the capability of Network and GIS-based visual approaches to provide significant information that cannot be simply extracted using pure statistical approaches. The findings not only highlighted significant mobility trends and different degrees of similarities at regional and local levels, but they also provided potential insight into the emergence of a pandemic on human behavior patterns and their likely socio-economic impacts, which can be further proceeded in future studies.

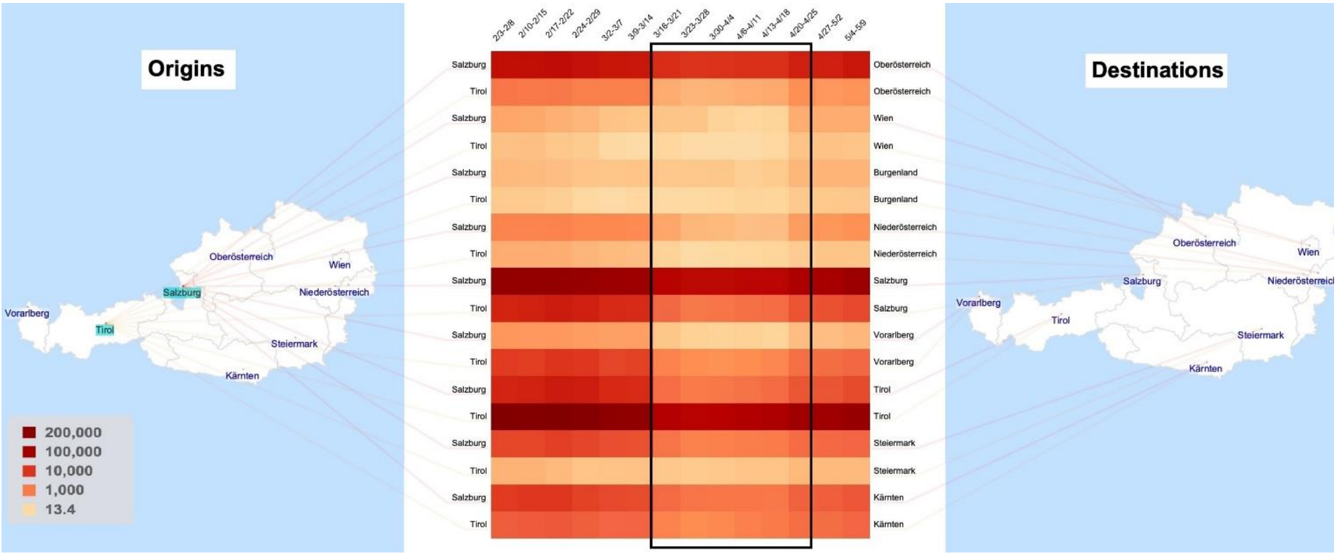

Figure 7. Spatio-temporal visualization of mobility flows magnitudes for selected regions (Lockdown period is indicated by the black rectangle)

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