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Robust Network Models for Mobility Analysis: Validation from an Unstable Mobility in a Maritime Setting

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Abstract: The importance of human mobility in maintaining physical health is of emerging interest in research and practice. Technological advances in wearable technology enable us to monitor human mobility in out-of-laboratory settings. Although a large amount of human mobility data is available from wearable sensors, there is a lack of systematic methodologies for extracting useful knowledge on human mobility from the collected data. The objective description of the different status of mobility patterns to interpret different physical health levels especially remains challenging. In this paper, robust network modeling from our preliminary study is validated in a real-world scenario with stable and unstable mobility conditions. The models based on population analysis utilize mobility data and extract distinctive mobility characteristics. Correlation networks and population-based analysis are utilized to efficiently examine the natural variability of human movement. Results demonstrate that the proposed robust network models identify mobility pattern changes in maritime conditions.

Keywords: Mobility parameters, Population-based analysis, Physical health assessment.

1. Introduction

Human mobility is fundamental to the physical activity required for maintaining physical health. A substantial number of studies have recognized the importance of human mobility in health [1-3]. Moreover, the impact of mobility on a number of medical and physical properties has been established in several studies [ref 4-6]. For example, variability associated with muscle fatigue, joint problems, or neurological problems has been correlated to mobility characteristics, and mobility has been used as an efficient indicator of such conditions in other studies [7-8]. Capturing irregular mobility characteristics by performing a mobility analysis is commonly used to identify mobility impairment. Falling risk, for instance, has been widely monitored by the variability of mobility patterns in the elderly, and declining mobility intensity has been determined by balance disorders during mobility [9-10]. These studies have typically used multiple wearable sensors. Recent research has tried to utilize mobility data from wearable sensors to make informative decisions on inclusively addressing the multidimensional characteristics of mobility [11-12]. However, the importance of methodology in mobility analysis has not been significantly considered, and there is a lack of data analytics methods that systematically analyze mobility characteristics and interpret the results from clinical perspectives [17].

This problem motivated our preliminary study [24], which employed robust network modeling methodology to analyze human mobility patterns. The proposed model in the preliminary study focused on population-based analysis instead of individual granularity to infer useful decisions by considering individual patterns of the population characteristics.

Robust network models consider the natural variability of mobility. Variability is a crucial aspect of human movement that should be considered in mobility analysis [13]. However, the variability of mobility, including internal and external conditions, is difficult to assess by deterministic approaches such as Manhattan and Euclidean distance methods. Classification of mobility patterns into finite numbers of categories could be appropriate and useful for a more comprehensive analysis of mobility variations.

Robust models also provide robust decision criteria when determining clinically problematic mobility statuses. The decision criteria would be flexibly achieved if individual patterns could be compared to similar population characteristics. In our preliminary work [24], correlation analysis was selected to obtain population-based criteria. Correlation analysis, as one of several population-based analytics, takes into account the variation of mobility patterns for analyzing individuals' mobility patterns, based on their characteristics as related to a given population. Correlation networks measure the statistical relationships among items. Using correlation analysis, embedded associations among subject mobility patterns can be observed. Although correlation analysis cannot establish a causal relationship between mobility patterns, it can compare each mobility pattern with the others. When the association among different mobility signatures is interpreted, it is important to consider characteristics of identified groups with various descriptive and clinical information.

This paper introduces and describes the methodology to build robust network models for analysis, including three different ways of determining weights among nodes. First, pattern-based networks are used when multiple, distinctive mobility conditions are present. The Pearson correlation coefficient is used to define weights among elements in the correlation network. Second, the magnitude-based option is primarily utilized when only a single mobility condition is available when monitoring mobility patterns. The difference of magnitude is used to determine weights on the edges of the network. Lastly, the hybrid option is where both magnitude and correlation are sequentially applied to examine distinctive differences between clusters in the network. The last option is suggested when mobility data are obtained where mobility conditions are not clearly defined or reported.

The following chapters are organized as follows: Section II provides descriptive information of the three modeling methods including construction of the networks. Section III presents the experimental results of applying the proposed modeling methods. Simulated mobility data are used to demonstrate the conceptual feasibility of the proposed models and results from the validation study using collected mobility data. The last section concludes with contributions and limitations.

2. Robust Network Modeling

Three different weight determination methods are available to construct robust networks. Appropriate selection of the network modeling method is based on the nature of the mobility conditions and parameters when collecting mobility data.

2.1. Pattern-Based Mobility Model

Nodes in the network represent individual subjects, and the connecting edges, i.e., correlation coefficients, among nodes represent the significance of associations in mobility. Correlation networks are implemented using the genome data in bioinformatics research [8]. After determining specific thresholds, parts of the nodes are shown in clusters in the network. The highly connected nodes of the network have significant association or similarity in terms of mobility parameters used for network construction.

This pattern-based network model is constructed using the patterns of the mobility parameter values obtained from the individuals. The correlation coefficient calculated for all pairs of individuals ranges on a scale from negative one to positive one. A coefficient of negative one means total opposite directional correlation, and a coefficient of positive one means total positive correlation. In practice, a coefficient greater than 0.75 or less than -0.75 is considered a significant linear correlation. The significance of a correlation coefficient between any two individual pairs is estimated by the statistical significance parameter (p). A p value of less than 0.05 is a significant correlation. Additionally, the pattern-based model enables us to flexibly apply different sampling granularity such as minutes, hours, and days. Higher granularity obtained by integrating mobility data over more extended time periods improves the generalization of results, whereas utilizing precise time periods can provide better sensitivity to describe different mobility patterns.

Pattern-based mobility network modeling can be applied to mobility data from different conditions. The different mobility conditions include physical mobility conditions such as hard, soft, and unstable mobility platforms and different mobility contexts such as before and after injury, day and night, and during and after work. Pattern-based models can be used in a variety of mobility conditions to analyze the changes and characteristics of mobility by visually illustrating outcomes. Notably, it is strongly suggested that pattern-based mobility models be applied if the mobility data are collected from different mobility conditions. The robust network will be more efficient when it is built using a pattern-based mobility model when the mobility data are obtained from different environments.

2.2. Magnitude-Based Mobility Model

Nodes in the magnitude-based mobility networks represent individual subjects, and the nodes are connected by edges among any pair of two individuals using weighted magnitude difference (WMD). Table 1 illustrates simulated sample data based on the magnitude of a mobility parameter during four consecutive days of mobility monitoring. Edges are connected among nodes whose weighted magnitude differences are significant between any pair of two individuals. The significance of weighted magnitude difference can be flexibly defined based on the purpose of mobility analysis. Equation (1) is used to estimate WMD between two subjects, A and B, as follows:

$$\Delta WMD_{A\text{-}B} = |M_A - M_B| / 0.5\,(M_A + M_B) \times 100 \quad (1)$$

For example, the first subject took 300 and 3000 steps in two consecutive days, respectively, and the second subject took 3000 and 300 steps during the same days. The pattern-based model considers a weight for this two- subject pairing as a high negative correlation pair. However, the number (i.e., magnitude) of steps taken by these two subjects is also significant to explain the association of the pair. The two subjects are similar in mobility except that they have different mobility properties on these two days. The distinctive pattern of the magnitude difference is efficient to describe the similarity between the two, while avoiding elimination of the magnitude discrepancies.

The magnitude-based mobility model is recommended when the mobility data are collected under similar mobility environments. Since the magnitude-based model is not able to consider differences from different observations, a mobility experiment or monitoring is required to be performed under the equivalent condition. Then, WMD among any pair of individuals is calculated and represented as the edge in robust networks.

With the magnitude-based model, for example, robust correlational networks for concurrent weeks to observe mobility change can be analyzed. The method also can be extended to assist in preventive analysis of physical health through the correlational networks. Adjustment of the level of aggregation of the networks produces different cluster formations and weights of networks.

Table 1. Sample Mobility Data Representing 4-Consecutive Days of Mobility Level (left) and an Edge Weight Table (right) Based on Weighted Magnitude Difference.

	Sub1	**Sub2**	**…**	**Sub 30**
Day 1	42.3	…	…	84.0
Day 2	80.1	…	…	61.6
Day 3	28.1	…	…	89.4
Day 4	46.3	…	…	47.5
Mean	49.2	…	…	70.6

Edge No.	**Subject**	**Subject**	**Magnitude Difference**
1	Subj 1	Subj 2	0.17
2	Subj 1	Subj 3	0.08
…	…	…	…
434	Subj 28	Subj 29	0.23
435	Subj 29	Subj 30	0.15

2.3. Hybrid Mobility Model

The hybrid mobility model sequentially applies both pattern- and magnitude-based mobility models. Nodes in the hybrid network also represent individuals, and the connecting edges among nodes represent the significance of associations in mobility using both correlation coefficients and WMD. Both the pattern- and magnitude-based mobility models require conditions of mobility data when constructing the correlational networks. Although the conditions of mobility are crucial, available or existing mobility data are not always collected under well-controlled mobility conditions. To address this common limitation in collecting mobility data, both magnitude- and pattern-based networks models are applied to construct correlation networks.

In hybrid-based mobility, due to the insufficiency of complete information of mobility conditions, both the correlational coefficient and WMD are utilized to build the correlational network. The correlation networks are first built using the correlation coefficient between pairs of any of two individuals to connect the edges. When clusters are available, WMD between the subjects is estimated, and the subjects in that specific cluster are again clustered based on WMD [13-14]. The sequence between two models can be applied in another way by applying WMD followed by the correlation coefficient. Conceptually, the hybrid model has similarity to the overlying in communication networks [18]. Fig. 1 illustrates the hybrid mobility model construction with comparisons of before and after the clustering process.

We believe that the hybrid model can be applied when properties of the mobility samples collected are not well known. By considering both the patterns and the magnitude, the resultant correlational network has the most important edges, and the model can include all the vital mobility characteristics [16]. The pattern or the weighted magnitude difference between the subjects in the two sets of clusters should be significant enough to improve the model by overlaying. Otherwise, this may result in minimal information gain from the correlational network. Table 2 summarizes important characteristics of the three models.

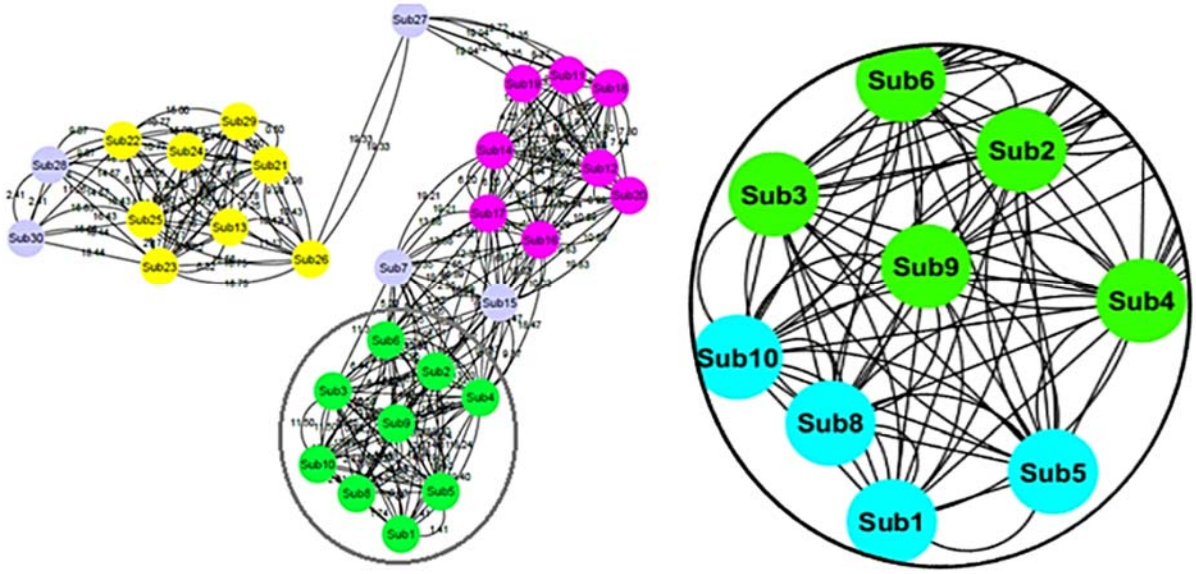

Fig. 1. Hybrid network by pattern-based clustering (left) and by magnitude-based clustering (right).

Table 2. Summary of Three Robust Network Modeling Methods.

	Pattern-based Mobility Model	**Magnitude-based Mobility Model**	**Hybrid-based Mobility Model**
Edge weight definition	Correlation coefficient between nodes	Magnitude difference between nodes	Combinatorial meaning
Mobility conditions	Need to control each experimental condition	Same experimental condition is fine	Need to control experimental condition
Treatment in Experiment	Heterogeneous experimental conditions	Homogeneous experimental condition	Heterogeneous experimental conditions
Sample size effect	Larger sample size is better to get robust correlation coefficient	Will not affect the robustness of network	Partial effect within clusters
Advantages	Robust population-oriented analysis	Comprehensive correlation analysis	Enables conducting an in-depth mobility mining
Disadvantages	Difficult to control heterogeneous experimental settings	Mobility characteristics can be excessively aggregated	Need to have heterogeneous experimental conditions

3. Experimental Study

In this section, two network models are constructed by using simulated and collected mobility data. The simulated mobility data are used to examine feasibility of the robust network model, and collected mobility data are applied to validate the model in stable and unstable mobility settings.

3.1. Feasibility Using Simulated Mobility Data

The advantages of using the correlation networks for constructing and analyzing human mobility networks are described in this section. Wearable sensor-based continuous mobility monitoring provides researchers and clinicians a better understanding of free-living mobility characteristics. Wearable accelerometers are wireless devices that capture unidimensional or multidimensional accelerometer data. A large amount of emerging research has been introduced to improve the efficiency and longevity of human mobility data processing.

To examine feasibility of the robust network models, simulated mobility data based on a realistic scenario are used. The process to construct the robust network additionally helps to improve reproductively of the robust network models by demonstrating how the correlation network can be used to analyze mobility data in a specific case study. In the simulated scenario, we consider a mobility monitoring of thirty nurses in a hospital setting, and robust correlation networks are constructed using the magnitude- based model.

The primary goal of this experiment is to examine associations by the magnitude of a mobility parameter among different subjects. The second goal is to illustrate how the cluster formation changes during different sampling periods. The first samples of different subjects are generated using the normal distribution with a mean value of 500 and 15.86 percent of a coefficient of variance according to the 68–95–99.7 rule [19].

To produce different mobility patterns across time, different mobility level reduction rates are applied to the simulated data. The first ten nurses exhibit a decrease in mobility by ten percent for every sampling period, the next ten nurses by twenty percent, and the last nurses by thirty percent. Simulated mobility data are shown in Table 3.

Table 3. Simulated Mobility Data Representing Mobility Levels during an 8-hour shift of Thirty Nurses.

	Sub1	**Sub2**	**…**	**Sub30**
Work start	553.78	…	…	384.85
2nd hours	498.40	…	…	269.40
4th hours	448.56	…	…	188.58
6th hours	403.71	…	…	132.01
Work end	363.34	…	…	92.40

Since we assume that simulated mobility data are collected in the same mobility environment including time and spatial conditions, the magnitude-based mobility model is appropriate to construct correlational networks. WMD among the thirty nurses is calculated for periodic time intervals (see Table 3). By applying a threshold of WMD of 20 percent, the networks are constructed as shown in Fig. 2, Fig. 3, Fig. 4 and Fig. 5. The first ten subjects are represented as green, the next ten as pink, and the last ten as red.

The robust network shown in Fig. 2 shows that all the nurses show similar mobility at the initial time period. After constructing the next robust network at the second-time period in Fig. 3, a subset of nurses (i.e., nurse-13, nurse-28 and nurse-30) belongs to a distinctive cluster in the network.

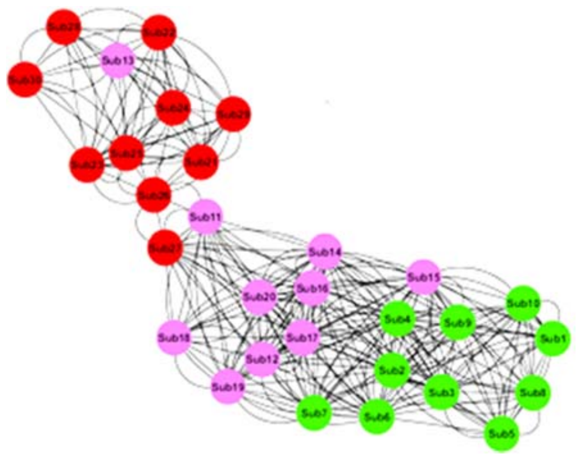

Fig. 2. Mobility network (work start).

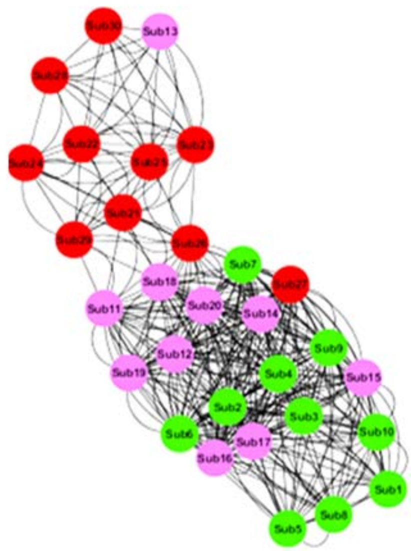

Fig. 3. Mobility network (2-hour shift).

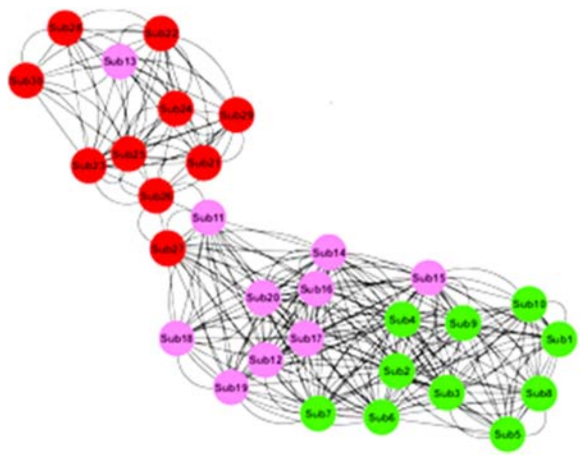

Fig. 4. Mobility network (6-hour shift).

By observing labels and node colors of the nurses in clusters in Fig. 4, the different mobility decline rates of the three groups of nurses are more clearly separated into two clusters as time progresses.

The robust network at the last periodic time interval in Fig. 5 efficiently describes the intended mobility differences by providing three distinctive clusters in the robust network. Each cluster is, finally, analyzed by given detailed mobility data to infer the underlying causes of the separation in the networks. For example, in Fig. 5, a cluster containing nurse-1 through nurse-10, shown in green, shows the higher mobility. The remaining two clusters display a lower mobility. The cluster with red color nodes shows the least mobility. Some subjects like nurse-7, nurse-15, nurse-27, nurse-28 and nurse-30 display an erratic mobility, because the nurse group contains a reasonable range of outliers outside of the normal distribution used to simulate mobility data.

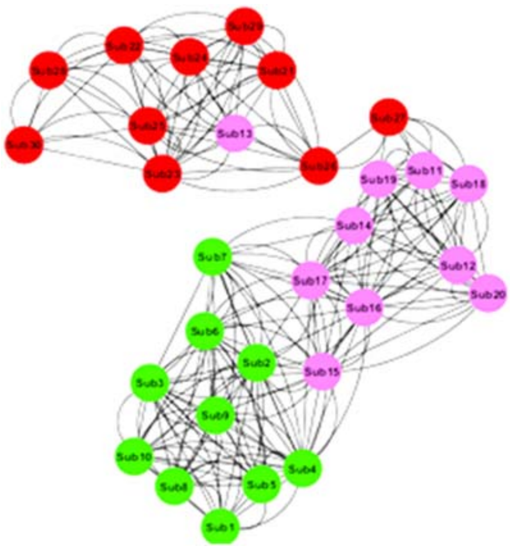

Fig. 5. Mobility network (work end).

In summary, mobility trend changes over time are efficiently described by using simulated mobility data. The robust networks along with time progression reveal that three different rates of mobility decrease as distinctive mobility characteristics of the group, although initial mobility levels of all thirty nurses were similar. Additionally, a few nodes showed an interesting transit among clusters that represent the natural variability of mobility patterns. Finally, two useful thresholds were identified to classify all nurses into active, moderate, and inactive mobility groups based on the population of nurses as a whole. These findings strongly support the proposed robust network analysis as an efficient population-based mobility analysis method.

3.2. Validation using Collected Mobility Data

The robust network models are applied to collected mobility data using wearable accelerometers in both stable and unstable mobility settings. Since the mobility data were collected in two different mobility conditions, the pattern-based mobility model was selected in this experimental study.

Data Collection. In total, 14 healthy college students between the ages of 22 and 26 years participated in the validation study. Table 4 shows the characteristics of the subjects. In the first session of the experiment, subjects performed functional balance tests including the Timed-up-and-Go test (TUG), Romberg Tandem test (RTT), and Functional Reach Test (FRT) to evaluate the balance function of each participant. The detailed information of the functional balance test is shown in Table 5. The second session for mobility data collection was performed on one of two training ships at Mokpo National Maritime University in South Korea. During the second session, acceleration data during mobility were collected using two accelerometers. These accelerometers were placed right above the lateral malleoli using elastic straps. All 14 participants walked in a stable condition when the ship was in the harbor, and walked in an unstable condition during a sea voyage. To collect acceleration data, participants wore three small and lightweight 3-axis accelerometers, called Shimmer3 [20]. Collected data were processed to extract appropriate mobility parameters from the raw acceleration.

Table 4. Descriptive Data of Participants for Stable and Unstable Mobility Experiments.

Characteristics	Descriptive data (Mean ± SD)
N	14
Female / male	2/12
Age (yrs)	23.2 ± 1.6
BMI (kg/m^2)	24.9 ± 1.8
Height (cm)	173.7 ± 6.7
Weight (kg)	73.6 ± 8.8

Mobility Parameter Extraction. To extract appropriate mobility parameters, the continuous acceleration data were first fragmented into acceleration data of individual steps. This process is commonly called step recognition, and peaks of acceleration from heel-strike actions are typically detected to recognize steps. The recognized steps, for example, are illustrated in Fig. 6 with red vertical dotted lines around peaks of vertical acceleration.

Once the raw acceleration was fragmented, the Mean of Vector Magnitude (MVM) and Symmetry of Vector Magnitude (SVM) were extracted as two key mobility parameters for constructing robust correlational networks. The vector magnitude of acceleration is estimated using Equation (2) below:

$$VM = \sqrt{(ACCx2 + ACCy2 + CCAz2)} \qquad (2)$$

Table 5. Summary of Three Functional Balance Tests.

Functional Balance Test	Description	Expected Outcome
Timed-Up-and-Go Test (TUG)	Test for assessing functional mobility that requires both static and dynamic balance control [21]	Higher functioning tends to achieve a shorter time period
Romberg Tandem Test (RTT)	Test to examine neurological balance functioning [22]	Higher functioning tends to maintain a longer time period
Functional Reach Test (FRT)	Test to assess of functional balance by measuring reach forward beyond arm's length [23]	Distance of arm position between standing and leaning forward

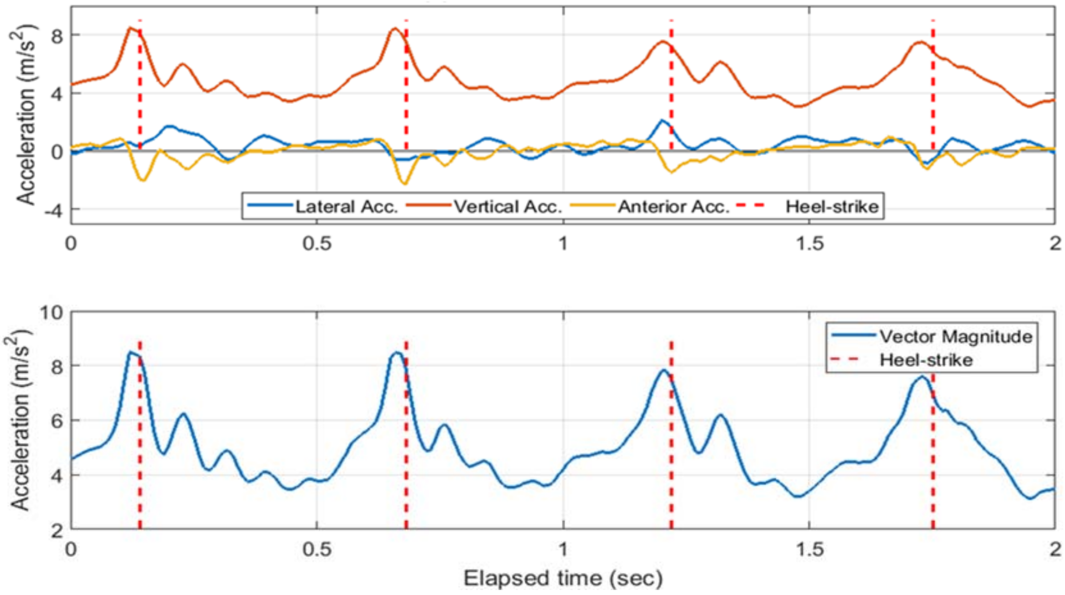

Fig. 6. Collected 3-D acceleration data (up) and step recognition results (down).

Step recognition and mobility parameter extraction algorithms were developed in the custom MATLAB 9.1 (Mathworks, Natick, MA) environment.

Correlation Network-based Analysis. Since the mobility data were collected in different mobility conditions (i.e., stable and unstable mobility platforms), pattern-based correlation networks have been applied to examine associations of mobility patterns between stable and unstable mobility environments.

Nodes in the sea mobility networks represent individual subjects and edges connect associated nodes based on correlation coefficients of four observations of mobility data. The significance of correlation coefficients between any two individual pairs was carefully examined by the statistical significance parameter (p). A value of statistical significance less than 0.05 was considered a significant correlation. Coefficient thresholds greater than 0.75 or less than -0.75 were considered significant linear correlation. Fig. 7 illustrates pattern-based correlation networks using MVM. MVM is an efficient mobility parameter to identify distinctive mobility characteristics between stable and unstable conditions. After constructing the robust network using MVM in Fig. 7, a subset of participants (i.e., H-4, H-5, H-8, and H-13) fall into an inappropriate cluster (i.e., stable mobility although unstable mobility data were given). The nodes of four participants are illustrated by red dotted circles. The balance functional test records of the participants show that the average of TUG and FRT results of the four subjects was 24.4 % and 18.3 %, respectively, below the average of all 14 participants.

Fig. 8 illustrates pattern-based correlation networks using SVM. SVM also efficiently represents the different mobility conditions of stable and unstable conditions. After constructing the robust network using SVM in Fig. 8, the same subset of participants (i.e., Node ID: H-4, H-5, H-8, and H-13) belongs to an inappropriate cluster. Based on the two robust networks, MVM better describes notable mobility differences compared to SMV in terms of mobility parameter efficiency.

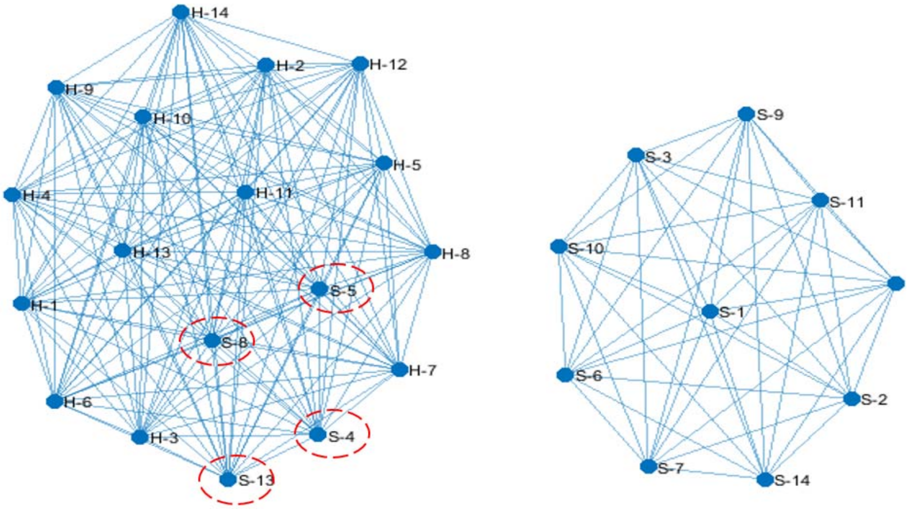

Fig. 7. Pattern-based correlation networks clusters of a stable mobility (left) and an unstable mobility (right) by using MVM.

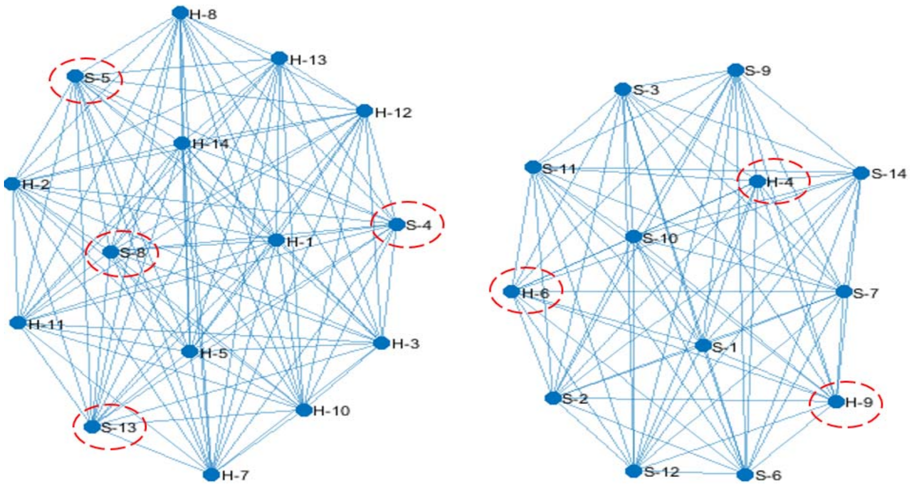

Fig. 8. Pattern-based correlation networks clusters of a stable mobility (left) and an unstable mobility (right) by using SVM.

4. Conclusions

There has been a lack of mobility data analysis methodologies while a large amount of human mobility data is available through wearable sensors. In this work, robust network modeling from our preliminary study has been validated in a real-world scenario such as stable and unstable mobility conditions. The robust models that are based on population analysis utilize mobility data and extract distinctive mobility characteristics for robust mobility characteristic descriptions. The use of correlation networks in relation to population-based analysis efficiently considers the natural variability of human movement. Results demonstrate that the proposed robust network models enable the identification of mobility pattern changes in a real-world scenario. Furthermore, distinctive clusters efficiently recognize distinctive mobility characteristics associated with physical health levels by assisting in the interpretation of results from a clinical perspective.

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