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Activity Recognition using Complex Network Analysis

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Abstract

In this paper, we perform complex network analysis on a connectivity dataset retrieved from a monitoring system in order to classify simple daily activities. The monitoring system is composed of a set of wearable sensing modules positioned on the subject’s body and the connectivity data consists of the correlation between each pair of modules. A number of network measures are then computed followed by the application of statistical significance and feature selection methods. These methods were implemented for the purpose of reducing the total number of modules in the monitoring system required to provide accurate activity classification. The obtained results show that an overall accuracy of 84.6% for activity classification is achieved, using a Random Forest (RF) classifier, and when considering a monitoring system composed of only two modules positioned at the Neck and Thigh of the subject’s body.

Keywords: body sensor network, complex network analysis, activity classification, wearable sensors.

1. Introduction

In healthcare applications, wearable sensors can be categorised based on the measured entity into subtypes that include biopotential sensors [1, 2], optical sensors [3, 4], stretch and pressure sensors [5, 6], chemical sensors [7, 8], and Inertial Measurement Units (IMUs) [9, 10, 11, 12]. Commercialisation of devices using the different subtypes of sensors has been gradually increasing. However, the most impressive commercialisation of wearable sensors in the past decade has been in the area of movement analysis and activity monitoring, using IMUs, due to the growing number of applications. The rapidly growing trend of self-monitoring and personalised healthcare led to an abundance of devices aimed at providing the user with simple quantifiable

information of activity levels, energy expenditure and sleep patterns [13, 14, 15, 16]. Studies using different constructed automated systems and aiming towards the identification and quantification of movement, under different conditions and for various applications, have also multiplied in the past couple of decades [18, 19, 20, 21, 22].

The ability to provide accurate and opportune information on the physical activities and behaviours of individuals is highly interesting in certain areas of healthcare. For example, patients suffering from physical disabilities or recovering from trauma might be required to follow strict regiments during their rehabilitation stages at home. Feedback from these sensors could help assess the patient’s performance and progress [23]. Furthermore, a better understanding of the progression and/or deterioration of physical activities could play a major role in early diagnosis, allowing for more efficient treatment and consequently lower healthcare costs.

1.1. Activity Recognition

Generally, research in the domain of activity recognition, regardless of the application considered, follows the scheme in Fig. 1. While several advances have been made in this domain, the large scope of sensors, methods and applications considered, has made it very difficult to properly identify optimal conditions for human activity recognition. That is not to say that activity recognition has not been achieved and validated in



Figure 1: General scheme of development of an activity recognition system.

several works. In fact, many studies have reported high accuracies in recognising different activities, under different acquisition protocols, and using different sensors. Table 1 gives a brief overview of some of the literature published in the past few years, showing sensor and sensor placement, protocol of acquisition, and the classification method. None of the recent literature, however, considers graph theory, or in other words complex network analysis, to explore the relationship between the sensors in the constructed monitoring system during the performance of different activities.

1.2. Complex Network Analysis

Complex network analysis is an approach that combines graph theory and statistical measures [36]. This type of analysis is concerned with real-life networks, which are usually characterised by an irregular and complex structure that continuously evolves with time [37]. The reason behind its growing popularity is that any discrete structure that results from the relationships between elements of real-life networks can be represented by a series of graphs. This is followed by topological characterisation of the obtained graphs, which is the process of representing each graph by a set of informative measures [38]. One application of complex networks analysis is the use of these measures to identify different classes of a structure. The

Table 1: Review of recent literature on activity recognition (IMU: Inertial Measurement Unit).

| Ref. | Sensor | Placement | Protocol | Classifier |
|-------------------|--|--|--|--|
| Bao 2004 [17] | accelerometer | arm, wrist, thigh, ankle and hip | 20 daily life activities | Decision Tree |
| Maurer 2006 [18] | accelerometer | wrist, belt, necklace, trouser pocket, shirt pocket, bag | sitting, standing, walking, ascending & descending stairs, running | Decision Tree |
| Ermes 2008 [24] | accelerometer | hip, wrist | supervised indoor & outdoor daily activities including sports, free unsupervised period | Hybrid (Decision Tree & Artificial Neural Networks) |
| Altun 2010 [25] | IMU: accelerometer, gyroscope, magnetometer | wrists, knees, trunk | 19 activities including Activities of Daily Living (ADL), sports & exercise | Bayesian Decision Making |
| Zhang 2013 [26] | IMU: accelerometer, gyroscope | hip | walking, ascending & descending stairs, jumping, running, standing, sitting | Sparse Representation |
| Mannini 2013 [27] | accelerometer | wrist/ankle | guided sequence of 26 laboratory-based activities and simulated daily activities grouped into 4 target classes | Support Vector Machine |
| Ahmadi 2014 [28] | IMU | shanks, thighs | series of actions of an outdoor sports training session | Discrete Wavelet Transform-based algorithm |
| Biswas 2015 [29] | IMU: accelerometer, gyroscope | arm | arm movements | K-means |
| Lee 2015 [30] | IMU | knee | daily activities and sports related activities | Random Forest |
| Ayachi 2016 [31] | Motion Capture Suit of 17 IMUs: accelerometer, gyroscope, magnetometer | 17 positions | 10 ADL | Discrete Wavelet Transform-based algorithm |
| Jalloul 2016 [32] | IMUs: accelerometer, gyroscope, magnetometer | ankle, arm, hip, neck, thigh and wrist | protocol of simple daily life activities | K Nearest Neighbour |
| Tao 2016 [33] | smartphone equipped with triaxial accelerometer | carried by subject | jumping, running, walking, ascending and descending stairs | multicolumn bidirectional long short-term memory (MBLSTM) classifier |
| Guo 2017 [34] | kinect camera and 17 inertial sensors | 17 positions | jumping, lying, running, sitting, standing, typing, walking | Library for Support Vector Machines (LIBSVM) [35] |

interest of applying this approach lies in its ability to define structural and functional properties of a network with dynamical units through simple measures that characterise the topology of the network. This type of analysis has been used in a wide range of applications such as the study of social networks and interactions [39, 40], brain connectivity analysis [41, 42], genetics [43], and transportation systems [44, 45], among others.

In this study, we discuss the construction of a structural connectivity network based on the correlation between a set of wearable sensing modules positioned at different parts of the body that constitute a monitoring system. The positioning of the sensing modules on the subject’s body takes on a natural network-like structure, which justified our interest in applying this type of analysis to explore the relations between the sensing modules during performance of activities. Specifically, the information provided by these relations can help further the understanding of how normal movement appears in the coordination between the different body segments and can help identify abnormal movements as a result. As such, this method could be very interesting in applications concerning movement disorders that manifest slowly over time such as in Parkinson’s disease patients.

Any network is defined by a set of nodes and links between the pairs of nodes. In this case, the sensing modules are considered to be the nodes of the constructed network, and they represent the different body parts at which they are placed. The correlation between the different body parts acts as the links between the nodes, representing the relationship between pairs of nodes while the individual performs various movements. The analysis performed on the network aims to classify a set of simple daily activities performed by healthy individuals. We have previously performed activity classification using the constructed system using a more conventional pattern recognition approach. The analysis performed and results of that approach are detailed in a previously published paper [32], and we aim to compare the performance of the pattern recognition approach with that of the complex network analysis in order to establish the validity of pursuing such an analysis technique. To our knowledge, the use of complex network analysis for activity monitoring and recognition of data collected through wearable sensors has not yet been applied.

In the following sections, we will describe the monitoring system used to collect activity data from healthy individuals. The connectivity analysis performed on the constructed network will be discussed in detail, and the results in terms of reduction of total number of modules in the system and classification accuracy will be presented.

2. Materials and Methods

2.1. Monitoring System and Acquisition Protocol

The monitoring system is constructed from six Shimmer3 IMUs [47] placed at the following positions of the subject’s body: dominant ankle, non-dominant thigh, dominant wrist, non-dominant arm, hip and neck (Fig. 2). Each IMU contains a low noise triaxial accelerometer (Kionx KXRB5-2042 600 ± 18 mV/g),

a wide range triaxial accelerometer (STMicro LSM303DLHC 1000 LSB/g at $\pm 2g$), a triaxial gyroscope (Invensense MPU9150 131 LSB/dps at ± 250), a digital triaxial magnetometer (STMicro LSM303DLHC 1100 LSB/Ga at ± 1.3), a temperature sensor and an altimeter. However, in this study, we only consider the data collected from the triaxial low noise accelerometer. In other words, our dataset consists of the three channel accelerometry measurements taken from six modules, resulting in a total of eighteen channels. Data was collected with a sampling rate of 512 Hz directly onto each IMU's memory card and no connections between the units were present.

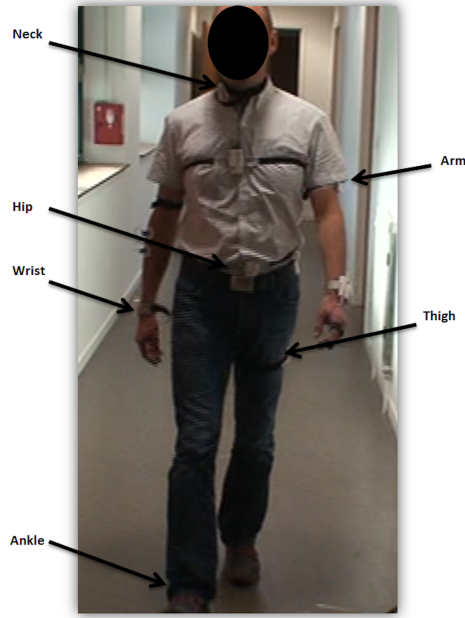


Figure 2: The placement of Shimmer3 IMUs on the subject's body. The units were physically attached using elastic strap.

An acquisition protocol, based on a series of simple daily life activities, was set up for the subjects to perform (Fig. 3). The activities were chosen to mirror realistic conditions of a subject's daily life in order to ensure simple repeatable measurements. Each activity was timed to approximately two minutes. The performed activities were finally grouped into four categories: walking, standing, lying and sitting.

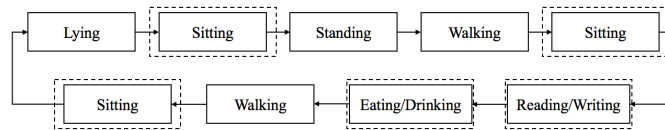


Figure 3: Protocol of simple daily life activities performed by each of the nine healthy subjects. The activities included in the dashed blocks are all classified as sitting.

Nine healthy subjects (four males and five females) performed the protocol during two sessions on two different days. The sessions were video-taped, and the exact start and end times of each activity were

annotated based on the collected video recordings. The subjects signed a consent form agreeing to the collection of data.

2.2. Preprocessing and Analysis Framework

The signal processing framework implemented is presented in Fig. 4. The scheme of analysis begins by collecting the three channel measurements of the low noise accelerometer located in each of the six sensing modules. This results in a total of eighteen signals that are segmented into smaller time windows for processing. In the interest of exploring the correlation between the different body segments during the performance of activities, the correlation between each two sensor channels for all module positions are computed for each time window. Following that, a connectivity matrix is computed to represent the correlation between sensor channels for each of the four activity groups and used to extract a number of network measures. The set of computed network measures are graphical parameters that represent quantitative descriptors of the connectivity matrix corresponding to each activity group. These measures are provided as input to the classifier in order to train in. Finally, classification is performed and a number of steps including evaluation of statistical significance and feature selection are implemented in order to minimise the total number of modules included in the system. We therefore perform the classification using the entire set of computed measures, in one case, and using the minimised set of measures after feature reduction techniques in another.

Each of the steps included in the signal processing framework will be presented in detail in the following sections.

2.3. Network Construction and Representation

Raw data was extracted from the triaxial low noise accelerometer of each module and grouped into the four categories of activities based on each activity's annotated start and end times. The data belonging to each group of activity is then segmented into $\Delta t = 7$ second time windows with a 50% overlap. The choice of window size used for segmentation has varied greatly in literature depending on the type of sensors used, their positioning and the nature of activities performed. As such, there is no consensus on an ideal window size. We based the choice of segmenting the data into 7 seconds on the study presented in [17]. Having similar sensor types, positions and activities it seemed reasonable to base the choice of window size on this study, also when considering its conformity to the duration of activities performed.

In order to construct the activity classification network, we designate each sensor axis in each of the monitoring system's modules as a node. The linear pairwise correlation is then calculated between each pair of nodes and acts as the weight function of the network, where the link between each pair of nodes is represented by the correlation coefficient:

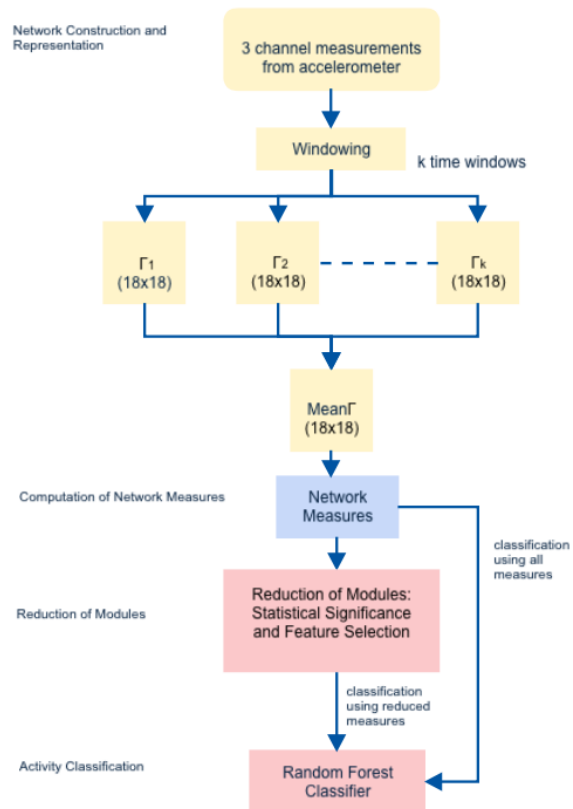


Figure 4: Processing scheme for the data collected from the sensing modules of the designed monitoring system.

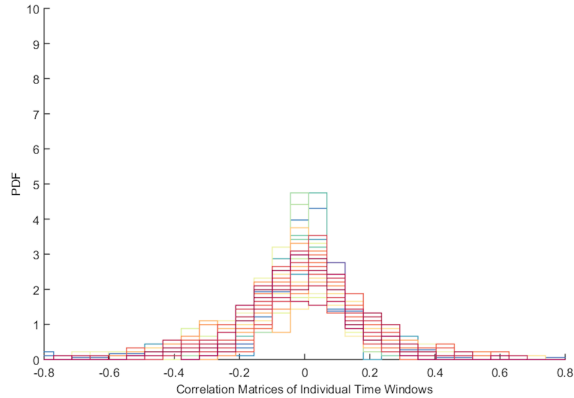


Figure 6: A plot showing the probability density function (PDF) of each correlation matrix corresponding to a single time window, for the activity of walking, on the same graph for comparison. The elements of each correlation matrix are binned into equally spaced containers.

of a unit circle and the links between them are represented by curved lines. In this visualisation, link weights are represented by the thickness of the drawn lines. Nodes are labeled based on IMU position and sensor channel. For example, the node "AnkleX" represents the ankle module's low noise accelerometer X channel, and node "ArmZ" represents the arm module's low noise accelerometer Z channel, and so on.

In Fig. 7, an example of the circular graph corresponding to a subject's single connectivity matrix for the different activity groups is shown. Some differences are visually discerned between the four activity groups, however interpretation can be quite difficult. Therefore, quantification of these observations is required through the computation of measures.

2.4. Computation of Network Measures

In order to quantify the topological differences between the networks corresponding to each of the activity groups, the computation of network measures is done. These measures are computed for each individual network element, which are the nodes and links. This, in turn, leads to the quantification of the connectivity profiles associated with these elements and reflects how these elements are embedded in the network.

However, network measures of all individual elements comprise a distribution which provides a more accurate and global representation of the network. This distribution is commonly characterised by its mean, which becomes essential in distinguishing between the different activity groups of the networks. Therefore, the mean connectivity matrix for each subject's data in each activity group is first calculated. The following network measures are then computed for each subject's mean connectivity matrix:

- **Degree:** the degree of a node is defined to be the number of links connected to it. This quantity represents the connectivity property of a node, revealing information on how it links to the rest of the

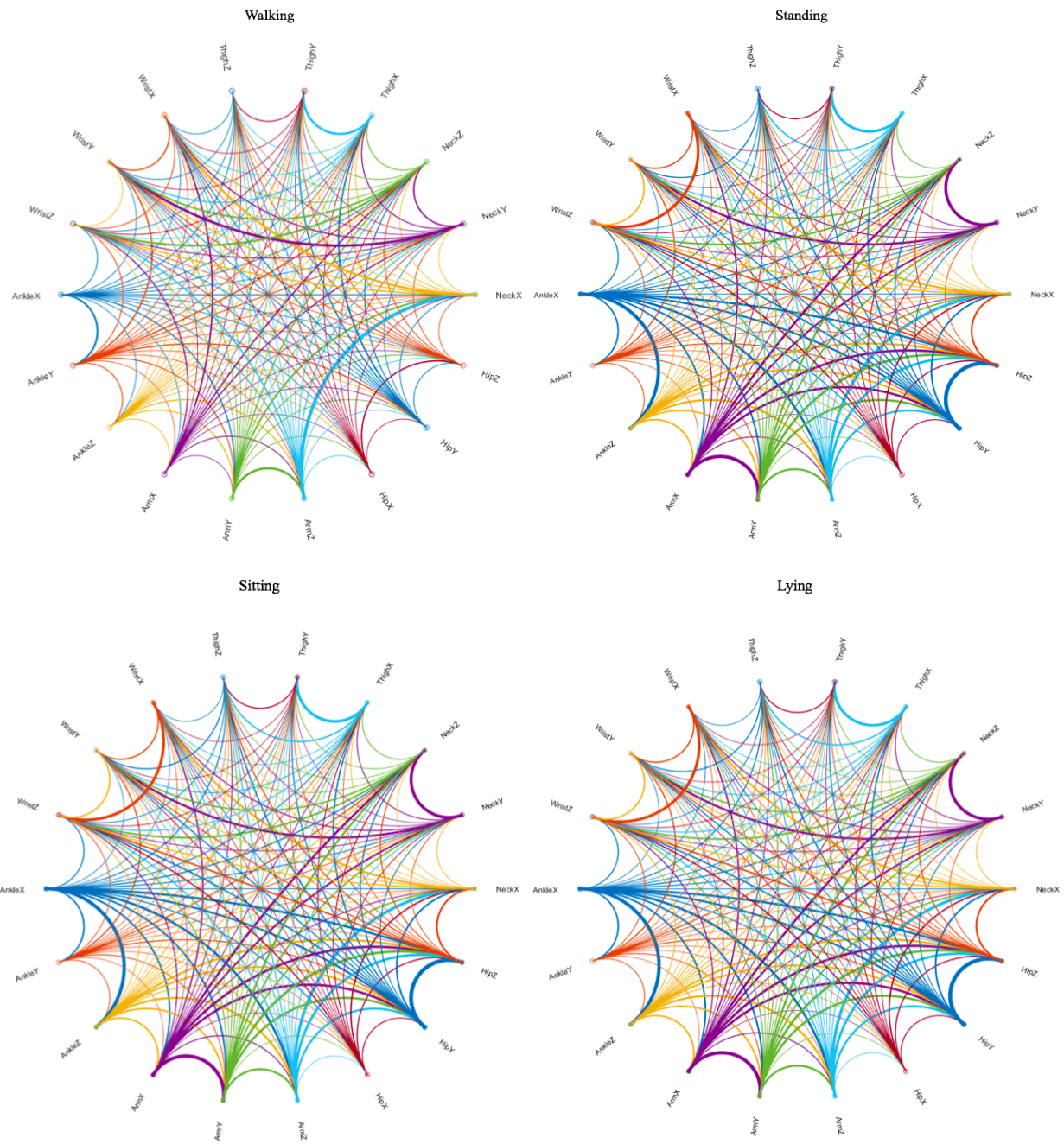


Figure 7: Example of the circular graph representation of the connectivity matrix obtained for each of the different activity groups. The connectivity matrix represented is the average correlation matrix obtained for the total number of correlation matrices per activity group. The strength of the correlation between any two sets of nodes is expressed by the thickness of the links.

network, or more specifically, revealing the importance of the individual node in the network. Assuming that a_{ij} is the connection status between nodes i and j such that $a_{ij} = 1$ if the link (i,j) exists and $a_{ij} = 0$ otherwise, then the degree of a single node i is computed as:

$$d_i = \sum_j a_{ij} \quad (2)$$

- **Strength:** the strength of a node is defined as the sum of weights of the links connected to it. Assuming that r_{ij} is an element of the undirected connectivity matrix, then the strength of a single node i is computed as:

$$s_i = \sum_j r_{ij} \quad (3)$$

- **Density:** the density of a node is defined as the ratio of present links to a node over the total number of possible links. Assuming that N is the total number of nodes in the network, and L is the number of links present in the individual node, then the density is computed as:

$$den_i = \frac{L}{\frac{N^2 - N}{2}} \quad (4)$$

- **Clustering Coefficient:** the clustering coefficient of a node is the quantification of the number of connections a node has with its nearest neighbours as a proportion of the total number of possible connections. If the neighbouring nodes to an individual node also form connections between themselves, then they appear to form a cluster. For a weighted connectivity matrix, the clustering coefficient is the average intensity of triangles around a network and is computed as:

$$C = \frac{1}{N} \sum_i \frac{2t_i}{d_i(d_i - 1)} \quad (5)$$

where t_i is the weighted geometric mean of the triangles around node i .

- **Modularity:** this value measures the density of links inside communities to links outside communities. In large scale networks, the optimal community structure is a subdivision of the network into non-overlapping groups of nodes, such that the number of "within-group links" is maximised and the number of "between-group links" is minimised. For a weighted connectivity matrix, the Modularity is computed as:

$$Q = \frac{1}{l} \sum_{i,j} (r_{ij} - \frac{d_i d_j}{l}) \delta_{m_i, m_j} \quad (6)$$

where m_i is the module containing node i , and $\delta_{m_i, m_j} = 1$ if $m_i = m_j$, and 0 otherwise.

- **Community Structure:** this property is based on a fast and accurate multi-iterative generalisation of the Louvain community detection algorithm [49]. It is considered that the optimal community structure is obtained when the network is subdivided into non-overlapping groups of nodes, such that the number of within group links is maximised and the number of between-group links is minimised. The Louvain community detection algorithm is used to extract communities from large networks and aims to optimise the value of Modularity as the algorithm progresses.

2.5. Reduction of Modules and Activity Classification

Each individual network is a representation of the global and local connectivity of the monitoring system. The computed measures reveal aspects of functional and structural connectivity between the IMUs, quantify the importance of individual IMUs, and characterise the relationship between them.

In certain cases, however, the values of many network measures are influenced by network characteristics, and are considered to be irrelevant or highly correlated. In order to avoid the effect that might have on the classification process, statistical significance methods are commonly implemented in order to test the importance of the computed measures [50].

In this case, the Kruskal-Wallis statistical test [51] was implemented. This type of statistical significance test is a rank-based non-parametric test which is also referred to as a "one way ANOVA on ranks". This method allows to test whether the samples originate from the same distributions without relying on specific distributions. This ensures the accuracy of the obtained significance even if the network fails to meet parametric conditions of validity.

For our constructed activity classification network, the test is implemented by comparing the computed measures of each node with respect to the four activity groups. The resulting p-value leads to assuming one of two hypotheses:

- Null Hypothesis H_0 : the samples belong to the same population
- Alternative Hypothesis H_1 : the samples belong to different populations

Where the population in this case represents the activity group.

Based on the obtained results, only the network measures considered to be statistically significant are retained for the classification process. This, in turn, results in minimising the feature set, removing noise in order to ensure better classification, and finally allows for the reduction of the number of IMUs in the monitoring system.

The reduced feature set of statistically significant network measures is then introduced to the classification phase. During this phase, classification was done using a Random Forest (RF) classifier with $n = 100$ trees [53]. The use of this classifier is based on analysis performed in a previous study [52] during which a

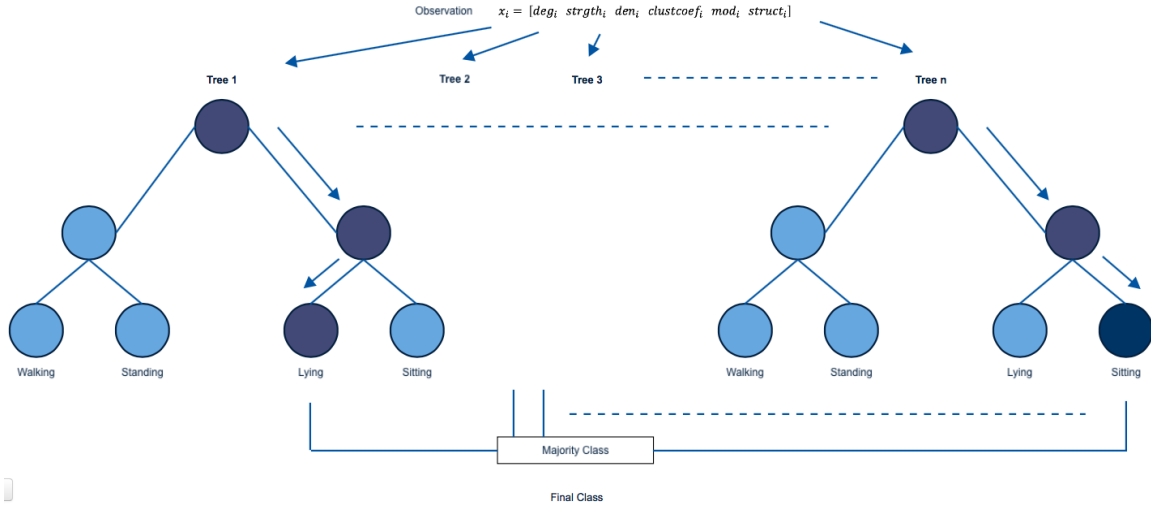


Figure 8: A simplified diagram of the operation of the RF classifier in classifying a single observation which is a vector of the computed network measures for a 7 second time window.

more conventional approach of feature extraction was performed. In that study, a comparison between a number of different classifiers was done and the best overall accuracy of activity classification was obtained when implementing the RF classification method. The same classification method was therefore retained in order to compare the performance of a complex network-based analysis method with that of a conventional feature-based analysis method.

An RF classifier is described as a combination of tree predictors [54]. It is an ensemble learning method for classification that operates by constructing a specified number of decision trees at the training time. Classification is based on the majority vote of this collection of decision trees, where each tree depends on the value of an independently sampled random vector with the same distribution for all trees.

Fig. 8 shows a simplified diagram of the operation of the RF classifier when classifying a single 7 second time window. In this case, we denote the observation as x_i , which is a vector composed of the computed network measures.

The advantage of this classification method is that, unlike decision tree classification, is that it aims to reduce the variance by averaging multiple decision trees trained on different parts of the same training set, thereby reducing over-fitting.

3. Experiment

The nine subjects performed the acquisition protocol on two separate days, resulting in two sessions per subject. However, due to data loss, the data collected from the first sessions of subjects #6 and #9, as well as the data collected from the second session of subject #8 are discarded. Hence the total number

of recordings over the two days for the two sessions is 15 (2 sessions x 9 subjects - 3 sessions). The mean correlation matrix computed for each subject’s data per session represents the network’s connectivity matrix. Therefore, a total of 15 connectivity matrices (18 x 18) were obtained per type of activity. The computation of the listed network measures resulted in a total of 108 measures (16 nodes x 6 IMUs) for the entire network. Hence, the dataset processed is composed of a 60 observations x 108 measures.

3.1. Activity Classification Using all Modules

Firstly, the performance of the activity classifier was evaluated using the entire feature set composed of the 108 computed measures. This was done under two different conditions:

- Condition 01: training was done using data collected from the subjects on Day 01 of the acquisitions and testing was done using the data collected on Day 02 of the acquisitions.
- Condition 02: training was done using data collected on Day 02 of the acquisitions and testing was done using data collected on Day 01 of the acquisitions.

3.2. Reduction of Modules

To reduce the total number of modules included in the final system, we performed two consecutive tests on the computed network measures. First, the Kruskal-Wallis statistical significance test was done on the entire set of network measures. The significance level, α , is initially set at 0.05 and the p-value is obtained for each of the network measures.

The resulting minimised set of measures whose p-values are considered to be statistically significant are then ranked through the ReliefF feature selection method [56]. This method allows us to explore the importance of each of the measures in the retained subset by assigning them weights according to their importance in distinguishing between the four activity groups.

4. Results

4.1. Activity Classification Using all Modules

The results of the classification under the two conditions are shown in Tables 2 and 3. As a measure of performance, sensitivity, specificity and accuracy for each group of activities are computed. In both cases, the overall accuracy of classification is about 88% and the sensitivity/specificity values of each activity group are almost identical. This proves the robustness of the activity classifier and its reliability in identifying the activity groups correctly regardless of the provided training and testing sets.

Table 2: Overall performance measures (%) obtained for the Activity Classification Network using the entire feature set (108 network measures) under Condition 01.

| Activity | Walking | Standing | Lying | Sitting |
|------------------|----------------|-----------------|--------------|----------------|
| Sensitivity | 88.1 | 85.2 | 94.8 | 86.6 |
| Specificity | 99.4 | 95.4 | 96.4 | 93.6 |
| Overall Accuracy | 88.7 | | | |

Table 3: Overall performance measures (%) obtained for the Activity Classification Network using the entire feature set (108 network measures) under Condition 02.

| Activity | Walking | Standing | Lying | Sitting |
|------------------|----------------|-----------------|--------------|----------------|
| Sensitivity | 85.7 | 85.8 | 94.3 | 86.0 |
| Specificity | 99.6 | 94.8 | 96.4 | 93.1 |
| Overall Accuracy | 88.0 | | | |

4.2. Reduction of Modules

4.2.1. Statistical Significance and Feature Selection

Prior to moving on with the classification process, the computed network measures are tested for statistical significance. In the Kruskal-Wallis test, significance level, α , is initially set at 0.05. A subset of 22 measures having p-values lower than the significance level α is obtained and considered to be statistically significant.

However, when considering methods that deal with multiple comparison such as the Kruskal-Wallis method, it is common to adjust the significance level α in order for the probability of obtaining at least one significance result due to chance is lower than the desired significance level. For that, we apply a Bonferroni correction [55] on the significance level α by dividing the original value by the total number of comparisons performed, which is equal to 18 corresponding to the total number of nodes. The new significance level, therefore, is $\alpha_{BC} = 0.0028$. The surviving subset of measures having p-values lower than α_{BC} consists of 10 measures instead of the original 22 (Table 4).

Measures corresponding to the Strength, Clustering Coefficient, Structure and Modularity were found to be statistically significant prior to the Bonferroni correction, while after the correction, only measures corresponding to the Strength and Clustering coefficient pertaining to only the Neck, Ankle and Thigh modules were retained.

The weights of the subset of measures are ranked in decreasing order in Fig. 9.

Following that, principal component analysis (PCA) was performed on different combinations of the ranked measures in order to determine a suitable subset while minimising the number of modules included. PCA is a statistical procedure that aims to identify strong patterns in a dataset and is often used to

Table 4: Statistically significant network measures for activity classification.

| Measure | Statistically Significant compared to α | Statistically Significant compared to α_{BC} |
|------------------------|--|---|
| Strength | AnkleY, NeckY, NeckZ, ThighX, ThighY, ThighZ, WristX, WristY, WristZ | NeckY, NeckZ, ThighX, ThighY, ThighZ |
| Clustering Coefficient | AnkleX, AnkleY, AnkleZ, ArmX, ArmY, HipY, NeckZ, ThighX, ThighY, ThighZ, WristZ, ArmY, | AnkleX, AnkleY, ThighX, ThighY, ThighZ |
| Modularity | ThighZ | |
| Structure | ArmY | |

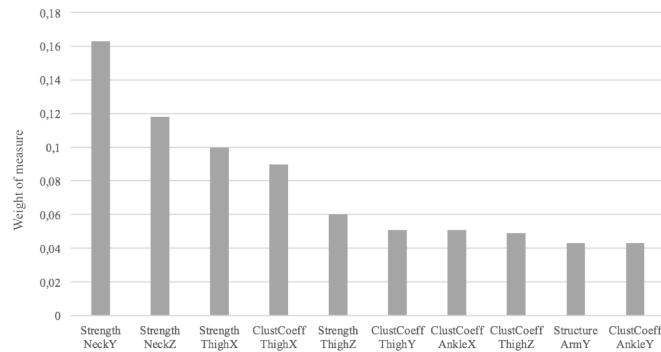


Figure 9: Ranking of network measures computed for the activity classification network in decreasing order using the ReliefF feature selection method.

visualise the data in an easily interpretable way [57]. This procedure is mainly used when dealing with high dimensional data, in which visualisation can be difficult. Its major advantage is reducing the dimensionality of the data by transforming it into a new coordinate system of a smaller number of uncorrelated variables, called principal components. In turn, this allows the identification of meaningful underlying variables. A common way of visualising the data after performing PCA is through a biplot, which is a plot that shows the principal components, represented by the axes, and the observed variables, represented by vectors. This plot shows the magnitude and sign of each variable’s contribution to the first two components, and how each observation is represented in terms of those components.

According to the results of the ReliefF feature selection, it was observed that measures corresponding to the Neck and Thigh IMUs held greater importance in this case for distinguishing between the four activity groups. Therefore the projection of observations was done while using different combinations of the highest ranked measures and the obtained clusters were observed. In Fig. 10, the projection of individuals shows grouping into distinct clusters belonging to each activity group. The correlation between these selected measures was also studied in order to eliminate redundancy in the information provided by them. As shown in Fig. 11, the correlation between the retained network measures is low, reiterating that each of these measures offers unique information relative to activity classification. The only two measures seemingly having relatively high correlation are those belonging to the neck module (StrengthNeckY and StrengthNeckZ). However, classification done by eliminating one or the other from the final subgroup ultimately resulted in slightly lower accuracy compared to having all five selected.

Based on this representation, the first five ranking network measures (StrengthNeckY, StrengthNeckZ, StrengthThighX, StrengthThighZ, and ClustCoeffiThighX) are considered for classification. This signifies the reduction of the total number of modules in the system to the Neck and Thigh modules only.

4.2.2. Activity Classification Using Two Modules

The classification strategy applied is based on splitting the healthy subjects’ data into a training and a testing set. The reduced feature set matrix is composed of 60 observations x 5 measures, and the subjects’ data corresponding to the first day of acquisition is used as the training set (TrainSet), while the data corresponding to the second day of acquisition is used as the testing set (TestSet). Table 5 shows an example of the contingency table obtained for one iteration, while Table 6 shows the obtained performance for this iteration.

Initially, classification using the entire feature set composed of the 108 computed measures resulted in an overall accuracy of 88.7% (Condition 01). However, the objective is to reduce the total number of modules included in the system. Therefore, we retest the classification performance using the reduced feature set composed of the selected five network measures corresponding to the Neck and Thigh modules. The overall performance of the classifier in this case is shown in Table 7. The mean accuracy for activity classification

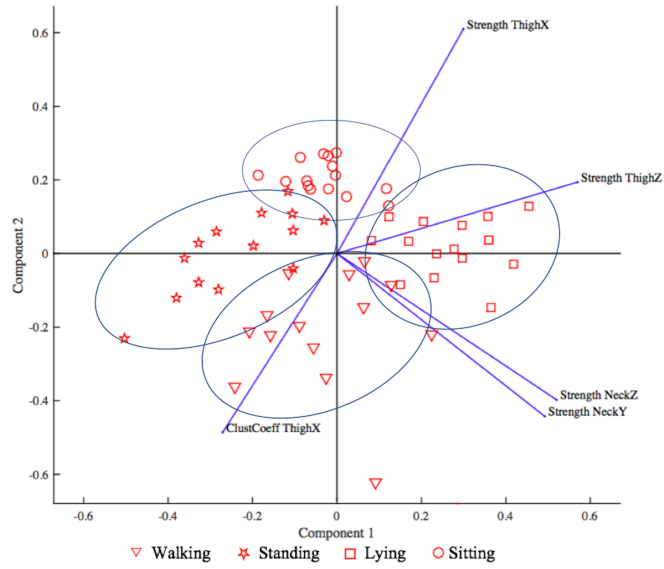


Figure 10: Biplot showing the projection of observations belonging to the four activity groups along with the selected network measures. Each set of observations belonging to the same group forms a distinct cluster.

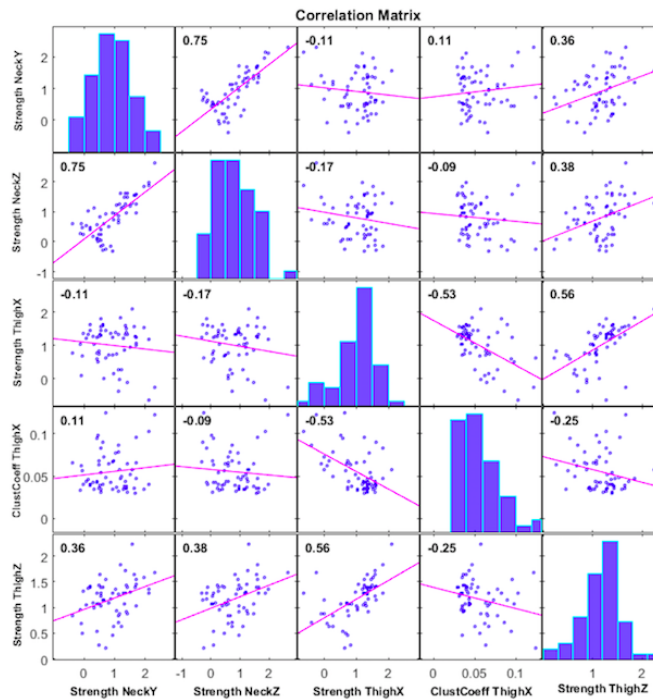


Figure 11: The correlation between the first five ranked network measures according to the ReliefF feature selection method.

Table 5: An example of the contingency table obtained for the TestSet.

| Activity | Walking | Standing | Lying | Sitting |
|-----------------|----------------|-----------------|--------------|----------------|
| Walking* | 6 | 1 | 0 | 0 |
| Standing* | 1 | 6 | 0 | 1 |
| Lying* | 1 | 0 | 8 | 0 |
| Sitting* | 0 | 1 | 0 | 7 |

Table 6: Performance measures obtained for the TestSet.

| Activity | Walking | Standing | Lying | Sitting |
|------------------|----------------|-----------------|--------------|----------------|
| True Positive | 6 | 6 | 8 | 7 |
| False Positive | 1 | 2 | 1 | 1 |
| False Negative | 2 | 2 | 0 | 1 |
| True Negative | 23 | 22 | 23 | 23 |
| Sensitivity | 75.0 | 75.0 | 100 | 87.5 |
| Specificity | 95.8 | 91.6 | 95.8 | 95.8 |
| Overall Accuracy | 84.3 | | | |

decreased slightly reaching 84.6%. Despite this slight deterioration in performance, however, we can still consider that the classification performance is satisfactory considering the achieved reduction of the number modules in the system.

Table 7: Overall performance measures (%) obtained for the Activity Classification Network using the reduced feature set (5 network measures).

| Activity | Walking | Standing | Lying | Sitting |
|------------------|----------------|-----------------|--------------|----------------|
| Sensitivity | 73.6 | 75.1 | 97.3 | 92.6 |
| Specificity | 95.0 | 93.3 | 95.3 | 95.8 |
| Overall Accuracy | 84.6 | | | |

4.3. Performance Relative to State-of-the-Art

To our knowledge, this is the first study in which graph theory or a network based approach has been used for human activity recognition using wearable sensors. This introduces some difficulty in comparing the obtained performance in our study with those in current literature. This comparison can therefore only be based on the classification accuracy obtained, and not on the processes and analysis leading up to that, since there is no available reference in literature to base that on.

Current literature based on more conventional approaches of processing, such as the ones reviewed in Table 1, have reported overall classification accuracies ranging from 72% to approximately 99%. It appears that the results obtained are highly dependant on the variable types of sensing modules, acquisition protocols, and processing techniques. As such, understanding the relative impact of a network-based analysis method in comparison to those studies is quite complicated.

However, when applying a more conventional time and frequency-based approach on the same dataset in a previous study [58], we obtained an overall accuracy of 95.6% using an RF classifier. While the obtained 84.6% in this analysis is a considerable drop in performance, we must consider the discrepancy in the total number of observations between the two studies, where the number of observations in the previous study is 2026. This signifies that the cost of misclassifying one instance in this study is much higher than in the previous study and can somewhat explain the difference in performance. However, this remains to be verified once a larger dataset is made available.

5. Conclusion

Many real-life networks are formed of large, complex connections that are neither uniformly random nor ordered. This principle led to the development of complex network analysis and its application on a wide range of connectivity data in several domains. However, to the extent of our knowledge, this type of analysis has not yet been applied in the area of wearable sensors for the evaluation of movement.

The designed ambulatory monitoring system is composed of a set of wearable sensors placed at different positions of the body, naturally taking on a network-like structure. Networks are characterised by anatomical or functional connections. In this case, the natural correlation occurring between different body parts during movement, whether corresponding to a specific activity or motor state, represents a functional connection between the monitoring system’s IMUs. This led to the interest of pursuing complex network analysis for this application.

The activity classification network was constructed based on the data collected from healthy individuals. The overall accuracy of activity classification for the TestSet was obtained at 84.6%, using network measures belonging to the Neck and Thigh modules only. These results show that module positions carry certain importance and the method of analysis applied has an impact on the choice of modules that are considered to be of higher importance.

In previous works, [32] and [52], we evaluated the classification of activities of the data collected from the same individuals and the same monitoring system using a more conventional pattern recognition analysis method. In this case, the overall accuracy of classification was obtained at 88.05% using the six modules, and a k -nearest neighbour classifier. In another pattern recognition based analysis, we performed classification using an RF classifier and an overall accuracy of 95.6% was obtained [58]. In this case, the classification

accuracy is significantly higher than that of the complex network analysis approach when using all six modules (88.7%).

However, this performance is still considered as encouraging. Moreover, the constructed network could be a useful tool for the prediction and appreciation of the modification of patient status, in a monitoring context. For instance, the modification of the strength of correlation, represented by the thickness of the links, could be useful in patient-follow up situations. A number of different steps are being considered to enhance the overall performance of the complex network approach. One of these steps is the computation of the non-linear regression coefficient which offers a distinction between the correlations (X,Y) and (Y,X) . Another issue, which we already attempted, is the thresholding and binary-transformation of the connectivity matrix. However, the results showed that considering a non-thresholded connectivity matrix is still favourable.

We concede that a major limitation for the classification process, in this study, is the small number of observations. This relates directly to the learning capabilities of the classifiers and affects the performance obtained. The low number of observations in this analysis is due to the short duration of activities and the low number of subjects included. The results obtained here, although promising, must therefore be considered as preliminary. Further exploration of this method of analysis will be done with a larger database that ensures the robustness of the classification process. More experiments need to be performed from a methodological point of view. To this respect, a clinical trial protocol has been developed at Biotrial and approved by an ethical committee. The acquisitions that will take place during this trial will help increase the population size and provide a more reliable understanding of the results obtained by this method.

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