COMPLEX NETWORK PROPERTIES OF EYE-TRACKING IN THE FACE RECOGNITION PROCESS
An Initial Study

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Abstract: In the paper, we propose to investigate eye-tracking sequences obtained in the face recognition process in terms of complex networks. A proper algorithm for transformation sequences coming from eye-tracking into complex networks is described. The analysis of parameters of obtained complex networks can be helpful in better understanding and classifying human mental behaviors and activities.

1 MOTIVATION

In this section we give motivations of our research on the application of complex networks in the analysis of eye-tracking sequences coming from experiments with the face recognition process.

1.1 Why Complex Networks?

The application of biometrics (eye movement belongs to this group) in interactive computer systems requires a response of the computer system to be realized in real time. Therefore, a dynamic analysis of human behavior (eye movement) becomes necessary. According to this necessity, there is a need to design dynamic models of creating tracks of eye movement during realization of mental processes interesting for us (for example, free viewing, recognition, browsing). The complex networks (Boccaletti et al., 2006) seem to be suitable to solve such a problem.

Another reason for using complex networks is connected with the possibility of the application of computer systems for the analysis of eyeball movement in the diagnosis process of human mental behavior (for example, in medical diagnosis). Therefore, there is a need to design methods and techniques enabling us to analyze structures of behavior patterns at length and to pick deviant behaviors (eyeball movement) up. We hope that the application of complex network theory in the process of the analysis of eye-tracking results will enable us to reach this goal. The aim of research carried out by us is to design a network model of eyeball movement and to apply all aspects of this process to parameters of complex networks analyzed in the framework of rules generally used in testing their properties.

1.2 Why Face Recognition?

Results of the first stage of research carried out by us are presented in this paper. The aim was to determine whether we deal with complex networks, and of which type, in the face recognition process. Selection of this mental activity in this research stage was not accidental. The analysis of literature showed that structures of eyeball movement tracks sprung from this kind of activity have a complexity degree which is not too high. It has the important meaning at this stage of examination of the effectiveness of the designed transformation algorithm, i.e., simplifying the process of comparison of structures obtained using the eye-tracker and structures obtained after the transformation process.

2 RUDIMENTS OF COMPLEX NETWORKS

The last decade has witnessed the birth of a new movement of interest and research in the study of complex networks, i.e. networks whose structure is irregular, complex and dynamically evolving in time, with the main focus moving from the analysis of small

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networks to that of systems with thousands or millions of nodes, and with a renewed attention to the properties of networks of dynamical units (Boccaletti et al., 2006).

In this section, we recall basic notions concerning complex networks and their properties. For more detailed information, we refer the readers to (Boccaletti et al., 2006).

Formally, a complex network can be presented as a graph either undirected or directed. In our investigations, we consider complex networks represented by undirected graphs. It means that we are not interested in directions of edges. An undirected graph $G = (\mathcal{N}, \mathcal{E})$ consists of two sets $\mathcal{N}$ and $\mathcal{E}$ such that $\mathcal{N} \neq \emptyset$ and $\mathcal{E}$ is a set of unordered pairs of elements of $\mathcal{N}$. The elements of $\mathcal{N} = \{n_1, n_2, \ldots, n_K\}$ are the nodes of G, while the elements of $\mathcal{E} = \{e_1, e_2, \ldots, e_L\}$ are the edges of G. The number of elements in $\mathcal{N}$ and $\mathcal{E}$ is denoted by K and L, respectively. The size of the graph is the number of nodes, i.e., K. In an undirected graph, each of the links is defined by a couple of nodes n_i and n_j, where $i, j = 1, \ldots, K$, and is denoted as (n_i, n_j). The link is said to be incident in nodes n_i and n_j or to join the two nodes. Two nodes joined by a link are referred to as adjacent or neighboring.

For a graph G of size K, the number of edges L is at least 0 and at most $\frac{K(K-1)}{2}$ (when all the nodes are pairwise adjacent). It is often useful to consider a matrix representation of a graph. A graph $G = (\mathcal{N}, \mathcal{E})$ can be completely described by giving the adjacency matrix $\mathcal{A} = [a_{ij}]_{K \times K}$, a square matrix whose entry a_{ij}, where $i, j = 1, \ldots, K$, is equal to 1 when the link (n_i, n_j) exists, and 0 otherwise. The degree k_i of a given node n_i is the number of edges incident with the node, and is defined in terms of the adjacency matrix $\mathcal{A}$ as:

$$k_i = \sum_{j}^{K} a_{ij}.$$

The geodesic from node n_i to node n_j in a graph G is the minimal number of edges connecting n_i with n_j. All the shortest path lengths of a graph G can be represented as a matrix $\mathcal{D}$ in which the entry d_{ij} is the length of the geodesic from node n_i to node n_j.

The following properties (parameters) of a complex network, represented by the graph G, are interesting for us (cf. (Boccaletti et al., 2006)):

- L - the average shortest path length of G:
$$L = \frac{K}{K-1} \sum_{i,j=1,\ldots,K, i \neq j} d_{ij}$$
- D - diameter of G:
$$D = \max_{i,j=1,\ldots,K} d_{ij}.$$
- C - the clustering coefficient of G:
$$C = \frac{\sum_{i=1}^{K} \frac{2L_i}{k_i(k_i-1)}}{K},$$
where L_i is the number of all edges existing between neighboring nodes of n_i.
- $\langle k \rangle$ - the average degree of a node in G:
$$\langle k \rangle = \frac{2L}{K}.$$

The most basic topological characterization of a graph G is expressed in terms of the degree distribution $P(k)$. The degree distribution $P(k)$ is defined as the probability that a node chosen uniformly at random has degree k. In real networks, $P(k)$ significantly deviates from the Poisson distribution expected for a random graph and, in many cases, exhibits a power law (scale-free) $P(k) \sim Ak^{-\gamma}$ with $2 \leq \gamma \leq 3$, where A is a factor of proportionality. The scale-free networks have a highly inhomogeneous degree distribution, resulting in the simultaneous presence of a few nodes (the hubs) linked to many other nodes, and a large number of poorly connected elements.

3 PROCEDURE

First of all, the aim of designing the transformation algorithm was to restrict an impact of the structure of stimulus on the obtained network structure during the analysis process. Therefore, the network has the form of an undirected graph. In our case, as distinct from the current methodology of analysis of eye-tracking results directed to analysis of a stimulus effectiveness (for example, testing the usability of the Web page), regions of interest have not been fixed a priori, equally for all of the subjects, but they have been created by the subjects during the realization of the face recognition process as important biometric elements. A structure of the obtained networks covers fixations, saccades, and transitions (Matos, 2010). The fixation lengths varies from about 100 to 600 milliseconds. During this stop the brain starts to process the visual information received from the eyes. Saccades are extremely fast jumps from one fixation to the other. The human visual field is 220°. The $1-2°$ area of foveal vision is about the size of a thumbnail on an arm lengths distance. Therefore, an estimate of the area of placement of the fovea is 2.4 cm. The last parameter affects a circle region of interest set in our algorithm. In the algorithm, we use the following notation, $R_r(c)$ is a circle region of interest (ROI) of radius r with the center at c, $card(X)$ denotes a cardinality of the set X.

Algorithm 1: Algorithm for transformation of a sequence of eye-tracking points into an undirected graph representing a complex network.

Input : $T = \langle t_1, t_2, \ldots, t_n \rangle$ - a sequence of eye-tracking points, r - a radius of a circle region of interest (ROI).
Output: $G = (\mathcal{N}, \mathcal{E})$ - an undirected graph representing a complex network.

$\mathcal{N} \leftarrow \emptyset$;
$\mathcal{E} \leftarrow \emptyset$;
$\mathcal{R} \leftarrow \emptyset$;
Create $R_r(t_1)$;
$\mathcal{N} \leftarrow \mathcal{N} \cup \{t_1\}$;
$\mathcal{R} \leftarrow \mathcal{R} \cup \{R_r(t_1)\}$;
for $i = 2, \ldots, n$ **do**
  $\mathcal{N} \leftarrow \mathcal{N} \cup \{t_i\}$;
  for $j = card(\mathcal{R}), \ldots, 1$ **do**
    if $t_i \in R_r^j(t_k)$ **then**
      $\mathcal{E} \leftarrow \mathcal{E} \cup \{(t_i, t_k)\}$;
      break;
    else
      Create $R_r(t_i)$;
      $\mathcal{R} \leftarrow \mathcal{R} \cup \{R_r(t_i)\}$;
    end
  end
end
Create an undirected graph $G = (\mathcal{N}, \mathcal{E})$;
Return G;

4 EXPERIMENTS

Investigations were conducted using Tobii T60 eye-tracker in laboratory conditions. This tool is able to measure human behavior (e.g. (Matos, 2010)) We have considered several problems (see (Jaskuła et al., 2011)). In the first problem five faces including both known ones (politicians, actors) and unfamiliar ones were shown to the subjects individually, each for a period of five seconds. The subject had the task to signal (by mouse clicking) the moment of recognizing a face (the moment when the subject became aware of this fact). In case of the unfamiliar face, signaling consisted in a lack of any reaction. In the second problem five faces including both known (politicians, actors) ones and unfamiliar ones were shown to the subjects individually, each for a period of five seconds. The faces were different from the faces used in the first problem. The subject had the task to lie, i.e., by signaling (by mouse clicking) the moment of recognizing the unfamiliar face or non-signaling the moment of recognizing the known face. The moment of lying was chosen arbitrary by the subject. In the third problem one unfamiliar face was shown to the subjects for memorizing for a period of five seconds. The face was different from the faces used in the previous problems. After 30 minutes, the subject had the task to recognize the memorized face out of five different faces. In case of recognizing the face (the moment when the subject became aware of this fact), the subject signaled the moment of recognizing by double clicking the mouse. In case of the unfamiliar face, the subject signaled the moment of making a decision about classifying it to this group, i.e., unfamiliar.

Each obtained eye-tracking sequence has been transformed into the graph representing the complex network according to the algorithm described in Section 3. An example of the complex network obtained in this way is shown in Figure 1. To display this network in the graphical form, a specialized tool called Pajek has been used (see (De Nooy et al., 2011)). Pajek is a program for the analysis and visualization of large networks. Next, parameters of the complex networks recalled in Section 2 have been calculated. Exemplary results of parameter calculations are collected in Table 1. Let us remind that L is the average shortest path length of the obtained graph G, D is diameter of G, C is the clustering coefficient of G, $\langle k \rangle$ is the average degree of a node in G, and N is the number of nodes in G.

Table 1: Results of parameter calculations.

Experiment ID	L	D	C	$\langle k \rangle$	N
#1	3.45	6	0.10	1.94	293
#2	3.41	7	0.14	1.70	294
#3	2.93	6	0.15	1.90	296
#4	3.49	7	0.13	1.89	282
#5	2.75	5	0.08	2.02	293

The degree distribution is calculated for $P(k_*) = k_*^{-\gamma}$, where k_* is close to $\langle k \rangle$. The smaller the value of γ, the more important the role of the hubs is in the network. In general, the unusual properties of scale-free networks are valid only for $\gamma < 3$. Exemplary results of degree exponent calculations for networks obtained in our experiments are collected in Table 2.

Table 2: Results of calculations of the degree exponent.

Experiment ID	γ
#1	1.54
#2	1.34
#3	1.52
#4	1.52
#5	1.61

The analysis of networks created on the basis of

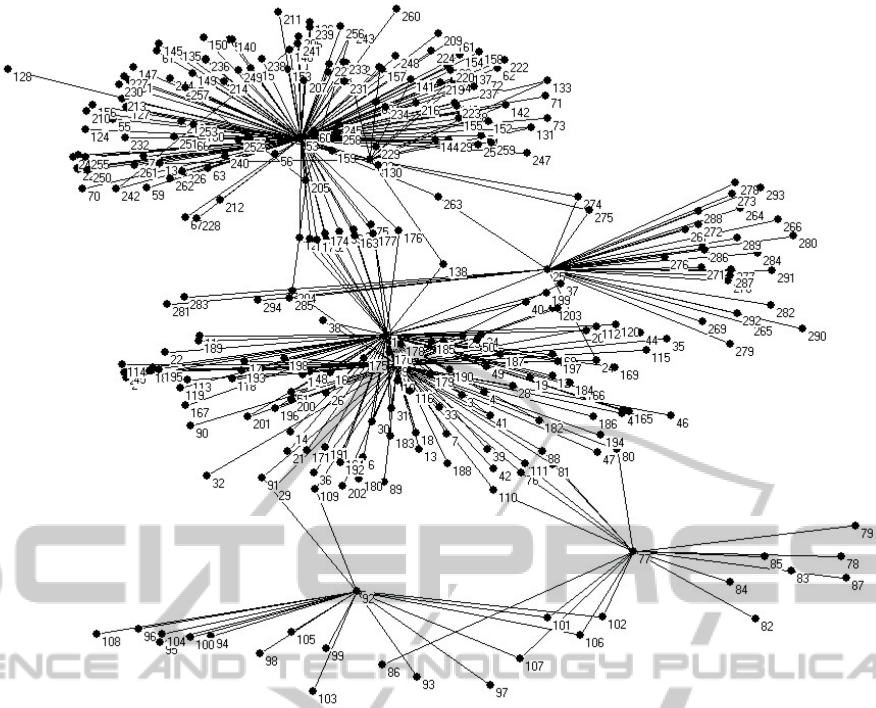

Figure 1: Example of the complex network corresponding to the face recognition process.

fixations (nodes) and cascades (edges) shows that scanpath structures originating in the face recognition process demonstrate properties of the scale-free networks. They are networks created by a large number of poorly connected nodes as well as a relatively small number of highly connected nodes that are known as hubs (Barabasi and Oltvai, 2004). This fact means (and simultaneously validates) that in the face recognition process, a crucial role is played only by some characteristic places (Van Belle et al., 2010). Probably, removing of such places complicates remarkably a proper recognition process or it even prevents it. Confirmation of this hypothesis is one of further research aims on the application of complex networks in the process of visual perception of human.

5 CONCLUSIONS AND FURTHER WORK

In the paper, we have started pioneering research on application of complex networks in the analysis of eye-tracking sequences coming from experiments with the face recognition process. Experiments showed that the complex network corresponding to the face recognition process can be treated as the scale-free network. In the future, we plan to investigate structures of the networks obtained from other mental activities (browsing, free viewing). We will also investigate dependencies between other parameters of the complex networks and characters of mental activities performed by the human. An important thing is to add methods and techniques of neuropsychology (EEG, computer tomography).

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