Contributions to the Modelling of Auditory Hallucinations, Social robotics, and Multiagent Systems

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Abstract

The Thesis covers three diverse lines of work that have been tackled with the central endeavor of modeling and understanding the phenomena under consideration. Firstly, the Thesis works on the problem of finding brain connectivity biomarkers of auditory hallucinations, a rather frequent phenomena that can be related some pathologies, but which is also present in healthy population. We apply machine learning techniques to assess the significance of effective brain connections extracted by either dynamical causal modeling or Granger causality. Secondly, the Thesis deals with the usefulness of social robotics strorytelling as a therapeutic tools for children at risk of exclussion. The Thesis reports on the observations gathered in several therapeutic sessions carried out in Spain and Bulgaria, under the supervision of tutors and caregivers. Thirdly, the Thesis deals with the spatio-temporal dynamic modeling of social agents trying to explain the phenomena of opinion survival of the social minorities. The Thesis proposes a eco-social model endowed with spatial mobility of the agents. Such mobility and the spatial perception of the agents are found to be strong mechanisms explaining opinion propagation and survival.

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Introduction

1.1 Personal introduction and motivation

Research is not static. It is a dynamic process where the reseacher might find themselves exploring paths that they did not expect in the first place as it is driven by the new discoveries, new areas, and new topics that might need to be addressed.

The original objective of my reseatch was to model brain plasticity using multiagent systems. The brain is quite a complex system and I wanted to explore the changes that can undergo in it when a part is wiped out, ie:a stroke, an accident,etc. and another needs to suply the function of the dissapeared part. In order to understand the brain's workings I started with a limited problem: to identify the underlaying structure of the auditory hallucinations' prone brain using rs-FMRI. I decided on this problema as this is a case where a section of the brain fire ups an internal stimulus that is understood as external, thus altering the function of said areas. This research ended up with promising results on the regards of finding differences on brain conectivity between hallucionation prone brains and those which are not. However, when trying to model this findings in a multiagent setting there was no good result as the brain sections and their conectivity is not as well defined as one could expect, and differences in neurotypical brains are the norm.

Seeing that this was a too complex of a point to start with multiagent modelling which to the simulation of social phenomena, as it seemed an appropiate starting point where the opinion changes could be linked to function changes in damaged brains' areas. More especifically, the simulation of small communities' opinion spread on larger communities, similar to revolutions and trends becoming the general opinion, could represent how a small change could affect a more broad and complex system.

The researching process is dynamic, however, as said before, and while I was trying to figure out how could I model a process that is not yet totally understood and has little medical image evidence, another path opened in front of me. In contact with the oncologic hospital of Donostia and the association of parents of children with cancer - ASPANOGI- our research group bring three social robots (two AIBOS and a NAO) to the hospital in order to entretain the children and bring secure playig pals for inmunodepressed kids. There I learned about the social defficencies this isolated childrens suffer. Having no direct social contact is essential for their survival but this isolation period is detrumental to their social skills' development and adds difficulty to the healing process as the child can not comprehend why they can not have face-to-face interactions with their caretakers and friends, which hurts the childs mental state.

Our NAO robot, however, could bring social interaction, as it is easy to sterilize and is viewed by the children more like a pal than a machine. Thus, the social robotics' path started, trying to entretain and, at the same time, help the children develop their social skills and give them mental tools to face the difficult situation they found themselves in. Therefore, transforming the robot in a therapeutic tool. In little to no time this research expanded itself as there was little to none work already done in the topic and the GIC group started to collaborate with psycologist and pedagogs in the European Project CybSPEED.

And thus, my three legged thesis was born.

1.2 Auditory Hallucinations

Due to improvements in neuroimaging, study of the brain is now more accessible, bringing more extensive and detailed information. New discoveries about brain networks and its behaviors offer an enhanced understanding of several neural conditions that have been quite obscure until now. In this new research environment, the pathophisiological models of neural conditions have been reformulated in order to integrate all the recent knowledge. However, these models are still quite simplistic as the experimentation in this area is practically limited to observation with little room for modifications due to the ethical implication of dealing with human beings.

One of the previouslly mentioned improvements in neuroimaging techniques is Functional Magnetic Resonance Imaging (fMRI). This type of imaging has allowed deeper understanding of the functional connectivity of the brain regions, and their relation have been quantified through studies of task performing. Resting state fMRI (rs-fMRI), i.e. blood oxygen level dependent (BOLD) signal capture while the subject is doing nothing, allows to measure the fingerprint of brain activity at rest. Rs-fMRI data are acquired from awake subjects in a passive mind state. It is increasingly considered in study designs because it does not exclude subject beacuse of their cognitive abilities. Besides, confounds that may be induced by task interactions are avoided [32]. The patterns of brain connectivity at rest are also being considered as biomarkers for some neurological conditions and neurodegenerative diseases [23, 29, 70, 93]. The current study aims to obtain measurements of effective connectivity on rs-fMRI discriminating subjects with a history of Auditory Hallucinations (AH), as a further step from finding effects based on functional connectivity [11, 28]. Functional connectivity has been a very influential tool to study several brain diseases, such as mild cognitive impairment [1], Parkinson's Disease [167], hiperactivity [1], and Autism Spectrum Disorder [5]. Many studies reported in the literature was done using Electroencephalographic (EEG) data [2, 4, 3], however there is a lack of causality information which to some extent is provided by efficient connectivity[52]. In this work, the identification of effective connections is done computing either Dynamic Causal Model (DCM) [53] and Granger Causality (GC).

One of the neural conditions of strong interest are hallucinations as they are a particularly complex phenomena that involves many brain areas in complex interactions. The singular characteristics of each type of hallucination makes it difficult to achieve a concrete model, as hallucinations cannot be detected from outside the patient and, therefore, need some kind of feedback from the studied individual lowering the accuracy due to subjectivity. Furthermore, as in other matters regarding health, the manipulation of the patients is strongly limited.In this context, a way of simulating the process that leads to hallucinations could offer researchers an experimental ground where effects of parameter changes could be explored in an innocuous way and some predictions could be attempted leading to a better understanding of the phenomena. Computable models offering predictions that can be validated against real data may be constructed following the paradigm of multi-agent system modeling [129, 161, 136], where agent interaction can mimic the functional connection between brain regions leading to the generation of hallucinations.

Any perceptual experience that resembles a veridical one in the absence of external stimuli is considered an hallucination, regardless of the involved sense [9]. Hallucinations are neurocognitive disorders of strong public interest, specially Auditory Hallucinations (AH), whose generating mechanisms understanding has experienced a remarkable advance in the last years. Hallucinations are a particularly complex phenomena, involving interaction of many brain areas.The specific brain regions involved on each type of hallucination makes it difficult to achieve consensus on a unique generative mechanism hypothesis. In this Thesis I focus on AH as they are the most widely present in the variety of mental conditions where hallucinations have been reported, both clinical and non clinical.

The mechanisms of AH generation are still unclear because they appear in diverse healthy and diseased populations, so that cognitive and neuroimaging studies face diverse confounds that hinder empirical validation [139, 152]. Studies in different areas have tried to find explanations considering metabolic disturbances[75], alterations in grey and white matter volume [91, 153], associated genes [26, 62], reduced structural integrity and functional lateralization[162], and functional connectivity of a brain regions' network [10] using a variety of neuroimage techniques including functional activation imaging using positron emission tomography (PET) or fMRI[140, 79], and functional connectivity studies using rs-fMRI data[8, 119, 11, 28].

1.3 Storytelling and social robots

Social robots have shown benefits as assistant and tutors for children in various studies [51, 78, 124, 127, 133]. The interaction with the artificial entities provide a number of benefits in many situations, from lack of emotional load while teaching children with Autism Spectrum Disorders (ASD) [13], to low infection risk while providing emotional support in hospital settings. Robotic storytelling has been approached in the recent years from this perspective, for instance, using a nursing robot for storytelling in kindergarten [51] has shown cognitive benefits, even if storytelling was unidirectional, using recordings and with no possibility of interaction.

Concurrently, dialogue systems have shown a sudden spread in human-computer interface systems, as seen by the wide use of systems such as Siri, Echo, Alexa, and others. This spread is linked to the proven effectiveness of recently developed data-driven machine learning methods for natural language processing [130], as well as the use of Reinforcement Learning approaches for the training of the systems [142, 144, 96], and the reduction of human interaction during said training using different mechanisms such as adversarial approaches [97].

In this context the challenge of interactive storytelling automation is a very interesting one, not only because of its possible application, or the breath of opportunities for innovative research areas, but because of its particularities. Storytelling not only implies the narration of a specific plot but also the adaptation of said narrative to the interactuators that receive the story and a human-like transmission of it. These systems are deeply linked to a number of different research areas such as Dialogue Systems, Narrative creation and Social robots. However there is a lack of references on automated/robotic storytelling systems in the scientific community. Seems that the entire field has been thoroughly neglected. The work in this aspect of the Thesis is a step forward to test social robots as therapeutic tools via autonomous storytelling.

1.4 Opinion propagation and survival

The issue of social influence of the minorities, how they can maintain their characteristics and even produce a change of the majority towards accepting their specificities has been an intriguing question in sociology and cognitive science [104], but there are few attempts to produce computational models which can be used to assess the value of the diverse mechanisms and hypothesis proposed. The aim of this work, is to develop simulations where the early stages of the resistance against opinion homogeneity could be reproduced, in an attempt to better understand the underlying processes and the effect of the spatial behavior of the social actors.

A related field of research is that of influence propagation in social networks. The analysis of influence propagation through social media started from the consideration of phenomena such as mobs, riots or strikes [67] as pure physical phenomena, stripped out of psychological considerations. The same model applies to propagation of opinions, including advertising [65], where the research question was to determine the appropriate balance between marketing efforts and word-of-mouth propagation through personal social networks defined by strong and weak links. The two basic spread models of influence propagation over graphs are the Independent Cascade model (ICM) [65], and the Linear Threshold model (LTM) [67]. It must be noted that I do not deal with Influence Maximization (IM) [43, 87], which is the problem of finding the minimal subset of influential nodes (IM-seed nodes) with maximal influence, i.e. that affect the largest number of nodes in the network, where influence is computed by propagation in the network according to a spread model. Instead, I let the friendship graph to be dynamic, according to the actual agent perception of their surroundings. Our model can be conceptualized as an ICM with moving agents, and changing graph topology.

Multi-agent and dynamic-network models have already established themselves as suitable methods for analyzing "complex social systems" and to formalize models of real-world systems [100], however hard to validate against real data. Therefore, they are one of the most popular techniques to study the social dynamics [17, 61, 84, 126], even if other approaches as sociophysics [33], threshold models [82], and dynamic models [37] has been widely considered. I will use multi-agent simulation as a means to study the effects of opinion propagation and survival in social systems endowed with dynamic spatial behavior.

1.5 Publications

- Graña, M., Nuñez-Gonzalez, J. D., Ozaeta, L., & Kamińska-Chuchmała, A. (2015). Experiments of trust prediction in social networks by artificial neural networks. Cybernetics and Systems, 46(1-2), 19-34.

- Ozaeta, L., Chyzhyk, D., & Graña, M. (2015, June). Some results on dynamic causal modeling of auditory hallucinations. In International Work-Conference on the Interplay Between Natural and Artificial Computation (pp. 185-194). Springer, Cham.

- Ozaeta, L., & Graña, M. (2016, October). Agent-Based Spatial Dynamic Modeling of Opinion Propagation Exploring Delaying Conditions to Achieve Homogeneity. In International Joint Conference SOCO'16-CISIS'16-ICEUTE'16 (pp. 177-185). Springer, Cham.

- Ozaeta, L., & Graña, M. (2017, June). Agent-Based Spatial Dynamics Explaining Sustained Opinion Survival. In International Work-Conference on the Interplay Between Natural and Artificial Computation (pp. 137-146). Springer, Cham.

- Ozaeta, L., & Graña, M. (2017, June). Finding Communities in Recommendation Systems by Multi-agent Spatial Dynamics. In International Conference on Hybrid Artificial Intelligence Systems (pp. 577-587). Springer, Cham.

- Graña, M., Ozaeta, L., & Chyzhyk, D. (2017). Resting state effective connectivity allows auditory hallucination discrimination. International journal of neural systems, 27(05), 1750019.

- Ozaeta, L., Graña, M., Dimitrova, M., & Krastev, A. (2018). Child oriented storytelling with NAO robot in hospital environment: preliminary application results. Problems of Engineering Cybernetics and Robotics, 69, 21-29.

- Ozaeta, L., & Graña, M. (2018, June). On intelligent systems for storytelling. In The 13th International Conference on Soft Computing Models in Industrial and Environmental Applications (pp. 571-578). Springer, Cham.

- Perez, I., Rekalde, I., Ozaeta, L., & Graña, M. (2018, June). Proposal of Robot-Interaction Based Intervention for Joint-Attention Development. In The 13th International Conference on Soft Computing Models in Industrial and Environmental Applications (pp. 579-585). Springer, Cham.

- Ozaeta, L., & Graña, M. (2018, June). A View of the State of the Art of Dialogue Systems. In International Conference on Hybrid Artificial Intelligence Systems (pp. 706-715). Springer, Cham.

- Lekova, A., Dimitrova, M., Kostova, S., Bouattane, O., & Ozaeta, L. (2018, October). Bci for assessing the emotional and cognitive skills of children with special educational needs. In 2018 IEEE 5th International Congress on Information Science and Technology (CiSt) (pp. 400-403). IEEE.

- Graña, M., Ozaeta, L., & Chyzhyk, D. (2019). Dynamic Causal Modeling and machine learning for effective connectivity in Auditory Hallucination. Neurocomputing, 326, 61-68.

- Dimitrova, M., Kostova, S., Lekova, A., Vrochidou, E., Chavdarov, I., Krastev, A., ... & Ozaeta, L. (2020). Cyber-Physical Systems for Pedagogical Rehabilitation from an Inclusive Education Perspective. BRAIN. Broad Research in Artificial Intelligence and Neuroscience, 11(2Sup1), 186-207.

1.6 Outline of the Thesis

The remaining contents of the Thesis is as follows:

- Chapter 2 gives the definition of some mathematical tools that are used in Chapter 3, namely the definition of the approaches for the detection of effective connectivity in the brain based on resting state functional magnetic resonance imaging (rs-fMRI), the support vector machine (SVM) approach to classifier building, and the selection of the most salient effective connections as features for classification.

- Chapter 3 contains the works and results on the auditory hallucination biomarker identification based on rs-fMRI data. We explain the motivation and state of the art, the dataset used for the computational experiments, and the results of these computational experiments.

- Chapter 4 relates the experiences, and subsequent observations and conclusions extracted, on the use of social robots, namely the NAO, for therapeutic aims in several settings.

- Chapter 5 describes the work on opinion propagation and survival in social systems. The simulated systems are described in mathematical detail, and the results of experiments carried out using multiagent simulation software are discussed at length.

- Chapter 6 contains conclusions and directions for future research on each of the tackled areas of work.
- Appendix A contains the detailed flow diagrams of the systems discussed in Chapter 5.

Chapter 2

Mathematical tools

This Chapter provides a short overview of the main computational methods used in Chapter 3 to assess the effective connectivity between selected brain regions. First, I introduce the Dynamic Causal Modeling (DCM) approach, secondly the Granger Causality (GC), and, finally, the Support Vector Machines (SVM) classifier building approach. DCM and GC have been discussed as alternative or complementary effective connection modeling [54], the former as a generative model, the latter as pure data driven approach. Section 2.1 gives the mathematical definitions of DCM. Section 2.2 gives the mathematical definitions of GC. Section 2.3 summarizes the SVM aproach to build classifiers. Section 2.4 discusses the approaches for effective connection selection applied in Chapter 3.

2.1 Dynamic Causal Modeling

Dynamic Causal Modeling (DCM) was proposed as a bayesian estimation framework for the effective connectivity between brain regions in the framework of fMRI cognitive experiments [56, 57]. Its implementation is provided in the

SPM package for neuroimage processing[1]. In essence, DCM assumes a bilinear dynamic model of the neural dynamics. Formally:

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \sum_{j=1}^{m} \mathbf{u}_j \mathbf{B}_j \mathbf{x} + \mathbf{C}\mathbf{u}, \tag{2.1}$$

where $\mathbf{x}$ is the n-dimensional column vector of hidden neuronal states for the n brain regions considered, matrix $\mathbf{A}$ encode the effective connectivity between brain regions, $\mathbf{B}_j$ encode the changes in effective connectivity induced by external stimulus, and $\mathbf{C}$ the effect of external stimulus.

The actual fMRI signal is convolved with the hemodynamic response function for a better model fitting, but can be applied as such to electroencephalogram (EEG) data. The methodology has evolved during its application to several cases. Recently [56], the model was enlarged to take into account also the phase-delay information, i.e. computing the cross-correlation of spectra (cross-spectra) the result has real and imaginary parts. The real part is the so called coherence, that measures the agreement between the sources. The imaginary part contains information about the time lags between the sources. Formally, the DCM neural dynamics model (before the hemodynamic adjustments) has the form:

$$\dot{\mathbf{x}}(t) = A\mathbf{x}(t) + B\mathbf{v}(t) \tag{2.2}$$

where $\mathbf{x}(t)$ is the n-dimensional column vector of hidden neuronal states for the n brain regions considered, A is the time invariant matrix of interactions or effective connectivity between brain regions, $\mathbf{v}(t)$ is a vector of exogenous influences and endogenous influences, and B is the time invariant matrix of effects of these influences on the brain regions. The current DCM approach performs a bayesian estimation of the parameters in the spectral representation

[1] http://www.fil.ion.ucl.ac.uk/spm/

$Y(\omega) = K(\omega) \cdot V(\omega) + E(\omega)$ according to conventional assumptions, such as the spectral density [56] of the form:

$$g_v(\omega, \theta) = \alpha_v \omega^{-\beta_v} + g_u(\omega, \theta) \tag{2.3}$$

$$g_e(\omega, \theta) = \alpha_e \omega^{-\beta_e}. \tag{2.4}$$

Such model covers many forms of noise, including exogenous variates that can be deterministic $g_u(\omega, \theta) = \mathcal{F}(C \cdot u(t))$, where $\mathcal{F}(.)$ represents the Fourier transform. The expected signal spectra is

$$g(\omega, \theta) = K(\omega) g_v(\omega, \theta) + K^*(\omega) g_e(\omega, \theta), \tag{2.5}$$

that is a sampling of the true spectra with Gaussian error $g(\omega) = g(\omega, \theta) + N(\omega)$. The full generative bayesian model

$$p(g(\omega), \theta) = p(g(\omega) | \theta) p(\theta | m), \tag{2.6}$$

requires the specification of the prior beliefs about the parameter $p(\theta | m)$ distributions. The complex coherence function between two wide-sense stationary signals $s_i(t)$ and $s_j(t)$ with Fourier transforms $S_i(\omega)$ and $S_j(\omega)$, respectively, can be factorized into the correlation between the signal amplitudes and the dispersion of the phase-differences [56]:

$$C_{ij} = \frac{\langle \alpha_i \alpha_j \rangle}{\langle \alpha_i^2 \rangle \langle \alpha_j^2 \rangle} \times \Phi_{ij}, \tag{2.7}$$

where the signal amplitude is $\alpha_i = |S_i|$, and

$$\Phi_{ij} = \left(\int_{-\pi}^{\pi} p(\delta_{ij}) \sin(\delta_{ij}) \, d\delta_{ij} \right)^2 + \left(\int_{-\pi}^{\pi} p(\delta_{ij}) \cos(\delta_{ij}) \, d\delta_{ij} \right)^2, \tag{2.8}$$

where $p(\delta_{ij})$ is the density over signal phase differences $\delta_{ij} = \varphi_i - \varphi_j$. The generative model in the Fourier transform frequency space for the effective connection features [56] is developed looking for the mapping between exogenous neuronal signal $U_k(\omega) \in \mathbb{C}$ and the observable signal $S_i(\omega)$. This mapping is specified by the kernel transfer functions $K_i^k(\omega, \theta)$ and the spectral density of the statistically independent neural signals $\gamma(\omega) = \langle |U_k| \, |U_k| \rangle$. The cross spectral density between two signals is the sum of the contributions of the neural signals:

$$\begin{aligned} g_{ij}(\omega,\theta) &= \sum_k g_{ij}^k(\omega,\theta), && (2.9) \\ g_{ij}^k(\omega,\theta) &= \left|K_i^k\right| \left|K_j^k\right| \cdot \exp\left(j\left(\phi_i^k - \phi_j^k\right)\right) \cdot \gamma_k, && (2.10) \\ K_i^k(\omega,\theta) &= \int k_i^t(t,\theta)\, e^{-j\omega t} dt, && (2.11) \end{aligned}$$

where $\phi_i^k = \arg\left\{K_i^k\right\}$ is the phase-delay induced by the kernel transfer functions $K_i^k(\omega, \theta)$. For each connection, the coherence and phase delay features are the module and argument of the complex cross spectral density, i.e. $|g_{ij}(\omega,\theta)|$ and $\arg\{g_{ij}(\omega,\theta)\}$, respectively, whose frequency domain is discretized to form feature vectors.

2.2 Granger causality

Granger causality (GC) analysis extracts effective connection information from the multivariate linear autorregression analysis of the fMRI time series, i.e. fitting a linear autorregressive model :

$$\mathbf{x}(t) = \sum_{i=1}^{p} \mathbf{A}(i)\, \mathbf{x}(t-i) + \mathbf{E}(t), \qquad (2.12)$$

where p is the model order, which is fixed by minimizing some model complexity measure, like the Akaike Information criterion, $\mathbf{A}\left(i\right)$ is the autorregression matrix with time lag i , and $\mathbf{E}$ is a noise term. The collection of matrices $\left\{\mathbf{A}\left(i\right)\right\}_{i=1}^{p}$ contains the effective connection information. The linear model of Eq. 2.12 is tranformed into the frequency domain, i.e.

$$\mathbf{x}\left(\omega\right)=\overline{\mathbf{A}}^{-1}\left(\omega\right)\mathbf{E}\left(\omega\right)=\mathbf{H}\left(\omega\right)\mathbf{E}\left(\omega\right), \tag{2.13}$$

where$\mathbf{A}\left(\omega\right)$ is the Fourier transform of the autorregression matrices, $\mathbf{H}\left(\omega\right)$ is the so-called transfer matrix which contains all the effective connection information at the considered frequency range. To characterize each connection I will be using the Partial Directed Coherence (PDC) measure[16] defined as follows:

$$PDC_{ij}\left(\omega\right)=\frac{\overline{\mathbf{A}}_{ij}\left(\omega\right)}{\sqrt{\overline{\mathbf{a}}_{j}^{H}\left(\omega\right)\overline{\mathbf{a}}_{i}\left(\omega\right)}}, \tag{2.14}$$

where $\overline{\mathbf{A}}_{ij}\left(\omega\right)$ is the ij element of matrix

$$\overline{\mathbf{A}}\left(\omega\right)=\left(I-\mathbf{A}\left(\omega\right)\right), \tag{2.15}$$

$\overline{\mathbf{a}}_{j}\left(\omega\right)$ is the jth column of the same matrix, and H denotes the complex congugate and transpose operations. The PDC coefficients rank the saliency of causal interaction from jth time series to the ith a each frequency ω. To carry out this analysis I have used the Granger multivariate autoregressive connectivity (GMAC) toolbox [145].

2.3 Classification by Support Vector Machines (SVM)

Support Vector Machines (SVM) [22, 154, 95] have become the *de facto* standard classifier construction method in the neurosciences [88, 101, 107], the life sciences [27, 63, 83, 148, 165], and many engineering fields [92, 111, 117]. Given a training dataset composed of n-dimensional feature vectors $\mathbf{x}_i \in \mathbb{R}^n, i = 1, \ldots, l$ and corresponding class labels $y_i \in \{-1, 1\}$, (patients are labelled as -1 and control subject as 1), the objective is to build a discriminating function

$$f(\mathbf{x}) = sign\left(\sum \alpha_i y_i K(\mathbf{x}_i, \mathbf{x}) + w_0\right),$$

that will correctly classify new examples $(\mathbf{x}, y)$, whose class y is unknown. In this expression, $K(.,.)$ is a kernel function which reduces to an inner product in the linear SVM case, α_i is the weight dof the support vector $\mathbf{x}_i$. The SVM training process seeks the set of support vector weights providing the decision hyperplane that is maximally distant from the boundary samples of the two classes. When no linear separation of the training data is possible, the kernel transformation

$$K(\mathbf{x}_i, \mathbf{x}_j) \equiv \phi(\mathbf{x}_i)^T \phi(\mathbf{x}_j)$$

enables mapping of the decision hyperplane into a non-linear decision boundary in the higher-dimensional space defined by the implicit function $\phi(\mathbf{x}_i)$. This higher-dimensional space may be even of infinite dimension for some kernel functions, such as the Radial Basis Function (RBF) kernel. Training is achieved by solving the following optimization problem

$$\min_{w,b,\xi} \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{i=1}^{l} \boldsymbol{\xi}_i,$$

subject to

$$y_i(\mathbf{w}^T\phi(\mathbf{x}_i)+b) \geq (1-\xi_i),\ \xi_i \geq 0, i=1,2,\ldots,n.$$

In fact, $C > 0$ is a regularization parameter used to balance the model complexity and the training error. The support vector weights are found solving the dual optimization problem

$$\min_{\alpha} \frac{1}{2}\boldsymbol{\alpha}^T\mathbf{Q}\boldsymbol{\alpha} - \mathbf{e}^T\boldsymbol{\alpha},$$

subject to

$$\mathbf{y}^T\boldsymbol{\alpha} = 0,\ 0 \leq \alpha_i \leq C,\ i=1,\ldots,l$$

, where $\mathbf{e}$ is the vector of all ones, and $\mathbf{Q}$ is an $l \times l$ positive semi-definite matrix defined as

$$Q_{ij} \equiv y_i y_j K(\mathbf{x}_i, \mathbf{x}_j).$$

In this study I use the linear SVM, which is the minimal complexity approach requiring no kernel model selection procedures for parameter tuning. Performing model selection of kernel parameters introduces instability in the results, independent from the significance of the extracted features. Solving the dual problem, I obtain the contribution of specific sample vectors, the support vectors, to the construction of the decision function. In some cases it is possible to obtain qualitative information from the support vectors, when they can be interpreted as representatives of desired features. Due to the small size of the sample, I applied a Leave One Out (LOO) cross-validation strategy, repeated one hundred times. The SVM implementation is the Matlab version of LibSVM (`https://www.csie.ntu.edu.tw/~cjlin/libsvm/`).

2.4 Effective connection selection approaches

In the literature, effective connection selection has been carried out as a statistical inference process, where either *a posteriori* probability of the connections or some surrogate methods of null hypothesis distribution estimation were considered [54].

I consider this case a two class classification problem where the feature vectors are composed of the effective connection coefficients estimated by DCM or GC for each connection considered in the model structure. Therefore, the classification accuracy is taken as the effective connection selection goodness measure. Accuracy is defined as the ratio A=(TP+TN)/N, where N is the sample size, and TP and TN are the true positive and true negative responses of the classifier, respectively. I consider the accuracy over the test set responses in the LOO cross-validation process. The kind of cross-validation strategy providing optimal error estimates is problem dependent [15], though LOO may suffer from higher variance than other k-fold strategies when the classifier algorithm is highly unstable, I am compelled to apply it by the very small sample size. Additionally, I expect that the ranking of the effective connections would be relatively invariant to the cross-validation method. Notice that I do not need nested cross-validation because the linear SVM does not require model selection.

The validation process tries to ascertain the brain area effective connections network that is the best model for AH generation. Goodness of the model is measured by the leave-on-out (LOO) classification performance of classifiers built on the connection parameters (coherence and phase delay) estimated by DCM for each subject and specified structure. The selection of the AH model structure is therefore carried out as a wrapper feature selection model, where combinations of connections are tested separately and the one with the best LOO performance is selected as the best fitting model. Thanks to the small number of connections, I have been able to explore exhaustively all the possible combinations. The DCM module in the statistical parametric mapping (SPM) (http://www.fil.ion.ucl.ac.uk/spm/) has a bayesian model selection approach, but I have not made use of it.

2.4.1 Effective connection selection

The first collection of experiments evaluates all possible combinations of effective connections, where each connection features are all the DCM or GC coefficients. Let us denote $\left[c_{ij}^{k}\left(\omega\right);\omega\in\Omega\right]$ the DCM or GC coefficients for the effective connection between the i-th and j-th areas in the k-th subject, where Ω is the discrete set of frequencies at which the DCM or GC coefficients are given. For a given subset of connections $S\subseteq E$, where E is the set of edges of the fully connected graph between considered brain areas, the feature vector of the k-th subject is built up as follows: $C_k=\left[c_{ij}^{k}\left(\omega\right);\omega\in\Omega;(i,j)\in S\right]$. The classification cross-validation experiment is carried out over this dataset to obtain the accuracy value that measures the goodness of the connectivity represented by S. The connection subsets considered are shown in Figure 3.4.

Model selection in DCM corresponds to the identification of the significant effective connections. Traditionally, it has been carried out as a Bayesian inference process, where the connections whose *a posteriori* probability is above a threshold are deemed significant. This process relies on several probabilistic assumptions, such as the a priori models, which compromise reliability and reproducibility [50]. Therefore, I follow in this work a machine learning non-parametric approach, where model selection is carried out as a wrapper feature selection process using a non-parametric multivariate machine learning approach [12, 25, 30, 72, 74, 125, 164, 6].

I consider two class classification problem, i.e. SZAH and SZNAH, because the comparison with HC is not relevant here. Feature vectors are built gathering the effective connection parameters estimated by DCM for each connection considered in the model structure. Therefore, the classification accuracy is taken as the measure for model goodness. The connection features considered are the frequency specific coherence and phase delay, which are vectors of 32 components in the current SPM implementation.

2.4.2 Greedy selection of frequency connection coefficients

In the second collection of experiments, I carry out a greedy wrapper feature selection over the DCM and the GC cofficients at each specific frequency, in order to identify at which frequencies are working the effective connections Greedy selection starts with the single effective connection frequency coefficient achieving the greatest accuracy in the cross-validation of the SVM classifier. Succesive iterations add the specific frequency coefficient that provides greatest accuracy increase. Formally, initially I consider the set of all efficient coeffients for

$$C\left(0\right)=\left\{\left(i,j,\omega\right);\omega\in\Omega;\left(i,j\right)\in E\right\}, \tag{2.16}$$

I estimate the single feature cross-validation accuracies, i.e.

$$A\left(0\right)=\left\{a_{ij}\left(\omega\right);\left(i,j,\omega\right)\in C\left(0\right)\right\}, \tag{2.17}$$

where $a_{ij}\left(\omega\right)$ is the accuracy achieved by a classifier using the feature dataset $F\left(0\right)=\left\{c_{ij}^{k}\left(\omega\right)\right\}_{k}$ selecting the triple that provides maximum accuracy, i.e.

$$\left(i^{*},j^{*},\omega^{*}\right)=\arg\max_{\left(i,j,\omega\right)}A\left(0\right) \tag{2.18}$$

as the first feature. I denote $S\left(0\right)=\left\{\left(i^{*},j^{*},\omega^{*}\right)\right\}$ the initial feature set. After this initial step, the greedy selection iterates considering at each step the set of candidate features given by connection coefficents

$$C\left(t\right)=C\left(t-1\right)-S\left(t-1\right), \tag{2.19}$$

so that the next coefficient selected is the one that maximizes accuracy $\left(i^{*},j^{*},\omega^{*}\right)=\arg\max_{(i,j,\omega)} A\left(t\right)$ over a feature dataset built adding one feature to the previously selected features, i.e.

$$F\left(t\right)=\left\{S\left(t-1\right)\cup\left\{c_{ij}^{k}\left(\omega\right)\right\};\left(i,j,\omega\right)\in C\left(t-1\right)\right\}_{k}. \tag{2.20}$$

Therefore, the maximum number of cross-validation experiment repetitions is proportional to the number of connections and the number of frequency coefficients per connection. The greedy process stops when there is no increase in the accuracy adding a new feature, returning a feature set $S\left(T\right)$, where T is the number of iterations carried out.

Chapter 3

Auditory Hallucination modelling

This Chapter deals with works searching for biomarkers of auditory hallucinations using Resting State Effective Connectivity and Machine learning. Section 3.1 provides introductory information about auditory hallucinations to set the stage of the works. Section 3.2 describes the dataset used for the computational experiments. Section 3.3 describes the functional modeling underlying auditory hallucinations that supports the effective connectivity approach. Section 3.4 refers the experimental results obtained by the application of effective connectivity extraction and machine learning classification. Section 3.5 contains a discussion of the significance of the results. Finally, Section 3.6 provides some conclusions that will be complemented in Chapter 6.

3.1 Background on Auditory Hallucination

The auditory hallucinations (AH) are a common trait in psychiatric disorders. Particularly, auditory verbal hallucinations (AVH) are considered key symptom of schizophrenia, being reported by 60%-80% of patients with up to 25% cases of antipsychotics resistance [11] which had result in schizophrenia patients being the most studied group [135, 138, 103]. Nevertheless, other clinical patients groups [139, 9] too have been studies as this highly distressing symptom is part of other psychiatric disorders, as bipolar disorder and major depressive disorder [150]. Even in healthy population, AH and AVH, have a prevalence ranging between 3 and 15% [76, 156] which have warranted some research [157]. To understand this phenomenon, and to acquire better understanding of complex psychiatric illnesses having hallucinations as a core symptom, it has been proposed to identify the hallucinating brain functional network fingerprint [76], i.e. the functional connectivity patterns that characterize the brain of a person reporting AH even when he/she is not experiencing them.

Different models for AH pathogenesis have been proposed [110, 156, 105], yet the exact pathophysiology remains unclear. Early models contemplate AH as example of aberrant speech perception [68] or traumatic memories that the patient fails to inhibit [155]. However both models fail to explain all the variations in hallucination processes. Other models present AH as the result from a breakdown in corollary discharge [46] or suggest that AH result from greater perceptual bias to detect auditory signals [42]. As most of the models are not mutually exclusive there are ongoing efforts to integrate such models [156].

From the neuroimaging techniques effective connectivity analysis by DCM on fMRI data [40] and EEG data [39] shows that top-down inhibition was impaired in these patients. There have been studies in different areas trying to find an explanation considering metabolic disturbances [75], alterations in grey and white matter volume [91, 153], associated genes [26, 62], reduced structural integrity and functional lateralization [162]. There is also a variety of neuroimage techniques used in those studies, which includes functional activation imaged using positron emission tomography (PET) or fMRI [140, 79], and functional connectivity studies using rs-fMRI [119].

From a mathematical point of view, Friston [89] offers the hierarchical Bayesian modeling framework to explain the perceptual deficit involved in visual hallucinations, interpreted as a suboptimal convergence of the expectation maximization search for the maximum a posteriori interpretation of the perceptual input, guided by very broad prior expectations. However, this reasoning does not sustain any biologically motivated AH generative mechanism. The literature [9, 76, 155, 138] contains several proposals of AH generation mechanisms that are converging to consider the following factors: top down failure to identify a sensory signal as self produced and to control its onset, the bottom up confusion in language brain areas, and, finally, the emotional drive behind AH generation. Evidences to confirm such hypotheses come from cognitive experiments, such as dichotic listening speech perception paradigm [76], or voice distortion paradigms [156]. Increasingly, studies about AH include functional Magnetic Resonance Imaging (fMRI) in order to obtain complementary evidences [8, 11, 79, 139, 152] in the form of functional or effective brain networks showing impairment to/from the brain areas corresponding to the functional elements identified by the AH generation mechanisms hypotheses. These studies may deal with the brain while the AH are happening, or in AH-free resting state [139]. The former allows more precise identification of the generative mechanism functional activation, while the latter may provide clues about the AH prone brain fingerprint.

I have worked on the empirical confirmation of the AH brain fingerprint, by the estimation of effective connections between brain regions endorsing some kind of causal relation. The work done contributes a detailed review of abstract psychological models of AH generation found in the literature. These models are formalized graphically providing the basis for the selection of relevant brain regions for the subsequent study by DCM of effective connectivity between them. The results of DCM for the selected connections are the coherence and delay estimated values computed from their average rs-fMRI signals. The connectivity model selection is carried out in the form of wrapper feature selection, using Support Vector Machine (SVM) as the classification system in a Leave One Out (LOO) cross-validation approach. The resulting connectivity structure supports empirically the models of AH generation proposed in the literature.

3.2 Materials

3.2.1 Dataset

The dataset used for empirical experiments has been already exploited in [28] to find discriminant features based on functional connectivity and local activity measures, without taking into account effective connectivity. The dataset consists on rs-fMRI data from 68 men and women, ages 18-65 years, divided in three groups: (a) 26 schizophrenia patients with a history of AH (SZAH), (b) 14 schizophrenia patients without a history of AH (SZNAH), and (c) 28 healthy control subjects (HC). The Structured Clinical Interview for DSM-IV-TR (SCID) [49] was administered to confirm axis I diagnosis in patients and to rule out major psychiatric illness in healthy control subjects. AH severity was assessed with the psychotic symptom rating scale, AH sub-scale (PSYRATS-AH) [71].

Nearly all (n = 24/26) SZAH patients experienced verbal AH, as confirmed during the research interview and/or documented in the patients' medical records; verbal AH could not be confirmed in two SZAH patients whose imaging data were originally acquired as part of a different dataset. MRI data acquisition for each subject consisted of 240 blood oxygen level dependent (BOLD) volumes and one T1-weighted anatomical image. Detailed participant characteristics (e.g., age, gender, handedness, illness duration, medication profiles), inclusion/exclusion criteria, and image acquisition parameters are provided in [135]. Only six patients reported experiencing AH during rs-fMRI capture, therefore the study conclusions must refer to the general effective connection fingerprint of brains tha are prone to experience AH versus brains that not.

3.2.2 Data preprocessing

The process begins with skull removal using the brain extraction tool (BET) from FSL (`http://www.fmrib.ox.ac.uk/fsl/`). Images were manually oriented to the AC-PC line. The functional images were coregistered to the T1-weighted anatomical image. Using the Data Processing Assistant for Resting-State fMRI (DPARSF) (`http://www.restfmri.net/forum/DPARSF`) software package, the functional images were slice timing corrected, motion corrected (using a least squares approach and a 6-parameter spatial transformation), smoothed (FWHM=4mm), spatially normalized to the Montreal Neurological Institute (MNI) template (resampling voxel size = 3 mm $\times$ 3 mm $\times$ 3 mm), temporally band pass filtered (0.01-0.08 Hz) to remove very low frequency physiological noise and high frequency noise from non-neurological sources, and removed of linear trends. Mean BOLD time courses for head motion, global brain signal, white matter, and cerebrospinal fluid were regressed out before functional connectivity analysis. All the subjects had less than 3mm maximum displacement and less than 3º of angular motion.

3.3 AH generative mechanism

Early hypotheses contemplated AH as example of aberrant speech perception [68] or traumatic memories that the patient failed to inhibit [155]. However both hypotheses are unable to explain the variability in hallucination processes. Other authors present AH as the result from a breakdown in corollary discharge [46], or suggest that AH result from greater perceptual bias to detect auditory signals [42]. One of the most widely studied aspects of hallucination prone brains has been lateralization. Several studies have reported a reversed lateralization of cerebral activity during AVH, showing right inferior frontal activation when left could be expected, because the left-hemisphere is more relevant than the right in language production in most right-handed subjects. fMRI studies have shown that the stronger the right lateralization was the stronger negative emotional content of the AVH [139]. Anyway, early studies reported that the brain activity during AVH was the same as when hearing real voices, which suggests that AVH generate activity in the speech regions in the left hemisphere like real auditory input does. In this context, it has been observed that the right ear advantage (REA) is attenuated in schizophrenia patients, being more predominant in patients with hallucinations [76] implying that left language regions are always "tuned in" to the aberrant signals, and are, therefore, already engaged in processing. Furthermore, patients with AH showed difficulties in shifting the attention to the opposite ear, which implies a difficulty in achieving top-down executive control [158]. As most of the generative mechanisms are not mutually exclusive there are ongoing efforts to integrate them [156].

3.3.1 Abstract functional generative mechanism

The abstract functional generative mechanism [9, 156] encompasses six functional areas, which can be divided in three main groups as shown in the fig-

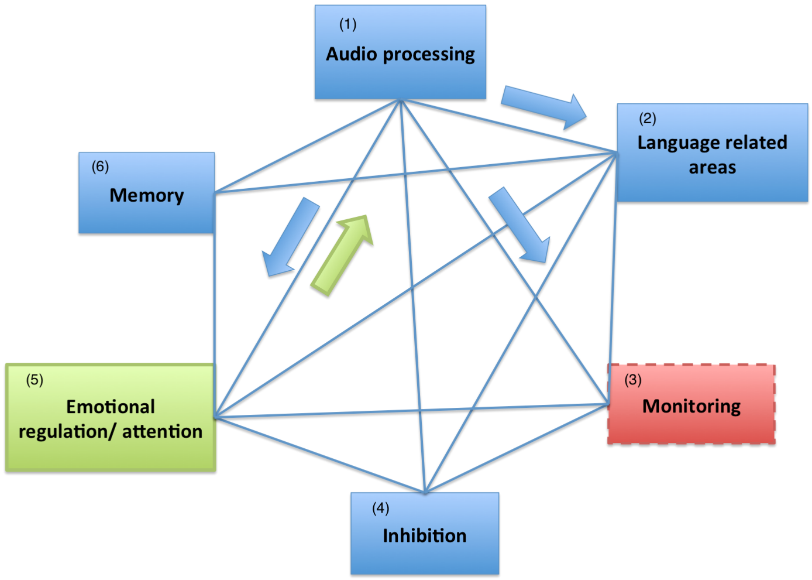


Figure 3.1: Abstract functional model of the brain functional interactions while experiencing an auditory hallucination. The arrows indicate the general expected hallucinating signal path, starting in the auditory cortex and traveling to emotional regulation/attention, language related and monitoring areas. The areas with thicker border are more activated in the hallucination prone brain, while areas with discontinued border are less activated.

ure 3.1: emotional regulation/attention (5) and memory (6) related areas, self-monitoring (3) and inhibition (4) areas, and audio processing (1) and language processing related (2) areas. The model tries to represent the "default" faulty network of a hallucination prone brain, not the event of experiencing the hallucination.

Regarding inter-area connections two important differences can be highlighted, considering bidirectional connections, also marked in the figure 3.1. On the one hand, aberrant hyper-activation has been found in the emotional regulation/attention (5) and memory (6) related areas, probably related to the common memories triggered and strong emotions contents often present in the hallucinations. On the other hand, lesser activation has been found in self-monitoring (3)/ inhibition (4) areas, explaining the monitoring error that impedes the brain to recognize thought and sensations as self generated, and the weaker capability of many patients to ignore the hallucinations. Audio (1) and language processing (2) related areas, however, have been reported function similar to the response to a real external signal, but with abnormal activations of language related areas of the left hemisphere. According to this model, the hallucinating signal originates in the auditory cortex, triggering the language related brain areas, and it is amplified by the emotional regulation/memory related areas. The under-activated monitoring/inhibition areas fail to recognize the signal as self-originated, consequently the phrases and voices are sharpened, so that the patient experiences them as hearing a real voice outside their head. This generative mechanism is related to the functional fingerprint network of the hallucination prone brain, which can be matched to effective connection networks extracted from rs-fMRI data, i.e. data not taken while experiencing the hallucination.

3.3.2 Anatomical network

The following brain areas have been identified in most reports and reviews [8, 157] as involved in AH generation:

- In the frontal areas, the left frontal operculum, both Broca's area and Broca's homologue, dorsolateral gyrus, right orbitofrontal gyrus, left middle frontal gyrus, and right precentral have been highlighted.
- In the subcortical areas, effects have been reported in the right putamen, cingulate (with particular interest to anterior cingulate, and left ventral and dorsal anterior cingulate, separately), hippocampal and right parahippocampal regions, right thalamus, and right amygdala.
- Some brain loci, such as the Heschl's gyrus (auditive area) [135] and the

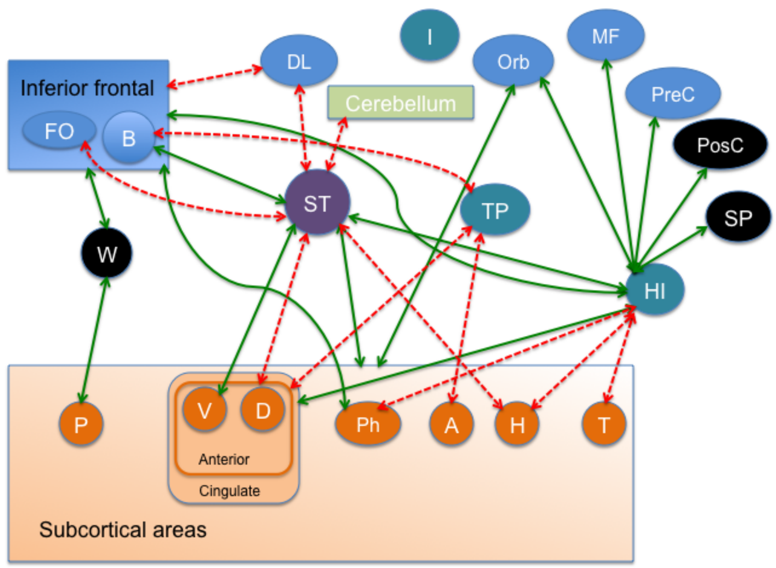


Figure 3.2: A detailed anatomical network of interacting brain regions underlying the abstract functional generative mechanism of auditive hallucinations. Continuous green line connections are stronger in the hallucinating brain. Dotted red line connections are weaker.

superior temporal gyrus have been hypothesized to be of importance in the hallucination mechanisms. Most studies that capture the data while the patient is experiencing AH report high activation of temporal areas, together with abnormal activation of anterior cingulate.

Figure 3.2 shows the graph of connections between anatomical areas identified in the literature. Areas color coded is as follows: light blue for temporoparietal, dark blue for fontal, black for parietal, and purple for temporal. In the figure, identified areas are as follows: orbitofrontal gyrus (Obr), frontal dorsolateral gyrus (DL), middle frontal gyrus (MF), precentral gyrus (PreC), Broca's area (B), frontal operculum (FO), superior parietal (SP), Wernickles area (W), postcentral gyrus (PostC), amygdala (A), Thalamus (T), putamen (P), ventral anterior anterior cingulate (V), dorsal anterior cingulate (D), hippocampus (H), parahippocamus (Ph), insula (I), Heschl's gyrus (Hl), Temporoparietal gyrus (TP), superior temporal (ST).

Summarizing, the main functional connectivity findings in the literature [8, 11, 28, 135] are: The superior temporal gyrus connections with left frontal operculum, dorsolateral frontal gyrus, left dorso anterior cingulate, cerebellum, and hippocampus is weaker in the hallucinating brain than in the normal brain. On the other hand, superior temporal gyrus connections with Broca's area, ventral anterior cingulate, and Heschl's gyrus are stronger in the hallucinating brain. The Heschl's gyrus of the hallucinating brain has connections of greater strength to most frontal areas, except the frontal operculum and dorsolateral gyrus, and the cingulate; on the other hand, it is more disconnected from some subcortical areas such as hippocampus, parahippocampus, and thalamus. Regarding the rest of the connections, the temporo parietal gyrus has been reported to have less connections with Broca's homologue, anterior cingulate and amygdala. Wernickle's area, in the other hand, is strongly connected to putamen and inferior frontal areas.

Figure 3.3 displays the simplified model that is being fitted by DCM to model the data, where I considered the four main regions: the Inferior Frontal (IF), Subcortical Areas (SbC), Anterior Cingulate (AC), and Superior Temporal (ST). It is based on the literature review and the connectivity results reported in [28] regarding the connectivity discriminant analysis of the data.

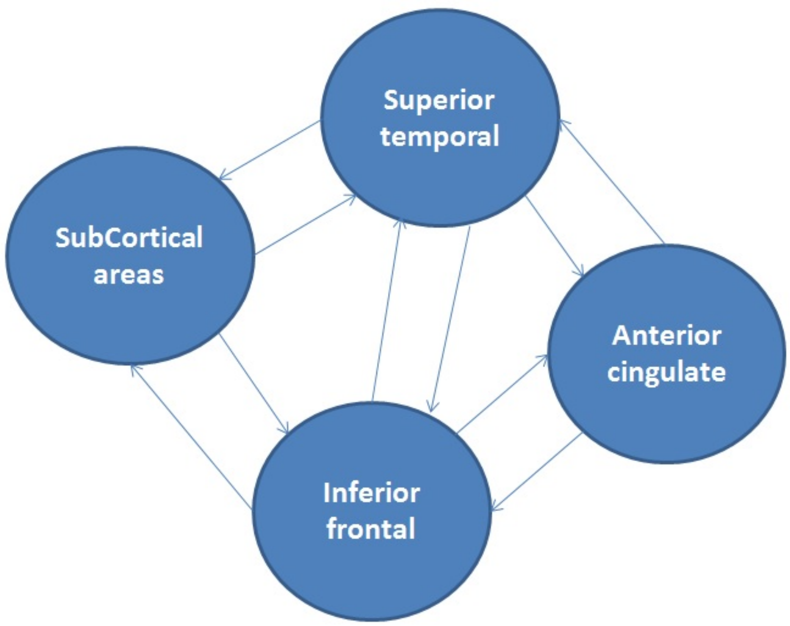
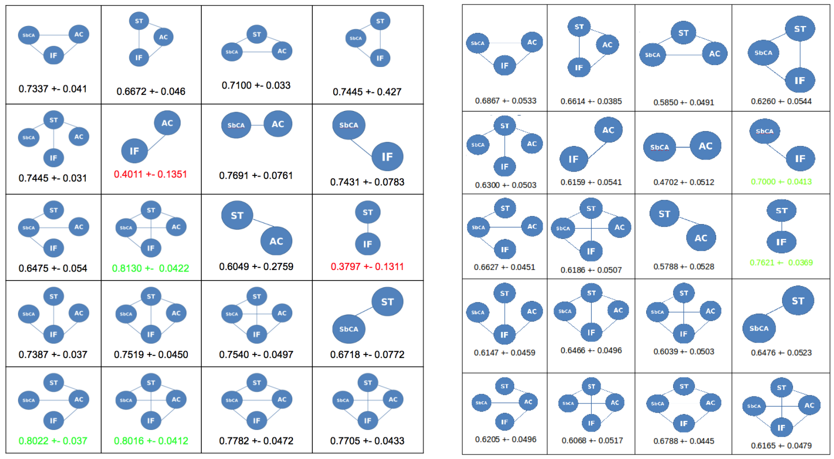


Figure 3.3: The simplified anatomical model of interacting brain regions used for DCM estimation of effective connectivity parameters.



(a) (b)

Figure 3.4: Results of the connection selection, testing all possible networks of effective connections. Below each network graphical representation, I give the average and standard deviation of accuracy results of cross-validation of a linear SVM classifier over their respective feature vectors. Average accuracy values above 80% and 70% for DCM-CCF and GC-PDC features, respectively, are highlighted in green. (a) Results using DCM-CCF features, (b) results using GC-PDC features. The features for each connection are the complete set of coefficients. Red values highlight results that are worst than a pure random classifier.

3.4 Experimental results

The implementation of DCM available in SPM has been set to work with task oriented fMRI data. However, it has been claimed that it can be applied to rs-fMRI [55], although there is no automatic process. To identify the volumes of interest (VOI), SPM proposes a first level analysis, which is not applicable to rs-fMRI data, because the General Linear Model (GLM) needs some experimental design. Therefore, I assume the VOI selection illustrated in Figure 3.3, already identified in Chyzhyk et al.[28], computing DCM-CCF and GC-PDC parameters for each subject and performing a wrapper feature selection to find the most discriminant network model.

The DCM and GC computational processes are applied individually to each subject, considering as representatives of the selected study areas shown in figure 3.3 the time series extracted from the following MNI coordinates: Anterior Cingulate (AC) (12, 30, 24), Superior Temporal (ST) (-18,-36,3), Subcortical Areas (SbCA) (12, -24, 9), and Inferior Frontal (IF) (-45, 9, 3). I extracted the following effective connection attributes as features for classification with SVM: the frequency specific delay matrix, the cross covariance function matrix computed by DCM (DCM-CCF), and the PDC computed by GC (GC-PDC).

3.4.1 Classification results

As it can be seen in the Figure 3.4, most of feature vectors extracted from the explored networks had an accuracy value close to 0.75. There are two networks whose cross-validation achieve accuracy worse than a random classifier, which are the ones composed of only one connection, IF-AC and the IF-ST networks. This could imply that these connections are more a source of noise and might be interesting to delete them from the classification. On the other hand, I found three networks that give an accuracy higher than 0.80: the complete networks removing (a) the IF-AC connection, (b) the SbCA-IF connection, and (c) the network of all the connections to the AC. One conclusion from these results is that more densely connected networks provided better results than networks with scarce connections. Therefore, I designed another set of classification experiments that follow a top-down approach in network complexity, deleting specific connections from the completely connected network.

The results of the first collection of experiments described in Section 2.4.1 is summarized in Figure 3.4, which shows all the networks of effective connections considered. Achieved average and standard deviation of classification accuracy estimated by LOO cross-validation is displayed below each network of effective connections. DCM-CCF results are shown in Figure 3.4(a). It can be appre-

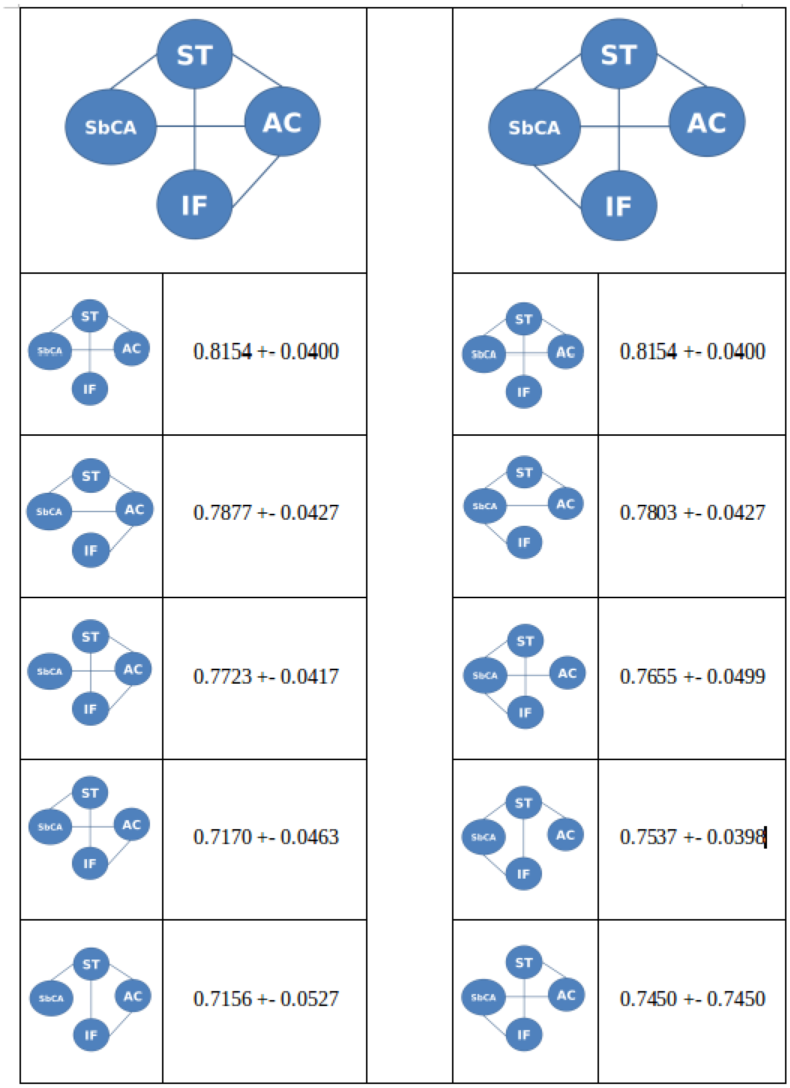


Figure 3.5: Average and standard deviation of accuracy for each combination of connections taking the two best structures from Figure 3.4(a) and trying to minimize them.

ciated that the linear SVM classifier achieves for most networks an average accuracy near 0.75. For two networks the classifier achieved average accuracy values which are worse than a random classifier, i.e. the IF-AC and the IF-ST networks. On the other hand, I found three networks whose average accuracy is higher than 0.80, they are obtained removing from the completely connected network the following subgraphs: (a) the IF-AC connection, (b) the SbCA-IF connection, and (c) the subnetwork of all the connections to AC. One conclusion from these results is that more densely connected networks provided better results than sparsely connected networks. Regarding results from GC-PDC features shown in Figure 3.4(b) it can be seen that results are much worse than those obtained from DCM-CCF features, barely reaching above 70% in some networks. A salient result is that the single connection networks IF-ST and IF-AC provide much better results for GC-PDC features than for DCM-CCF features. The most discriminant network achieved using DCM-CCF features is visualized in Figure 3.6.

These results imply that the connection more strongly related to the process of the AH are the ones associated to the ST area. This is in agreement with the models presented in Sections 3.3.1 and 3.3.2.

3.4.2 Greedy selection of frequency connection coeffients.

The second computational experiment deals with efficient connection coefficients at each frequency independently, carrying out a greedy wrapper feature selection as described in Section 2.4.2. The results are summarized in Figure 3.7. The plots for GC (blue) and DCM (green) features show the improvements achieved at each iteration adding to the set of features the effective connection coefficient at the specific frequency that provides the greatest increase in the average accuracy of the SVM classifier. Conversely to the previous experiment,

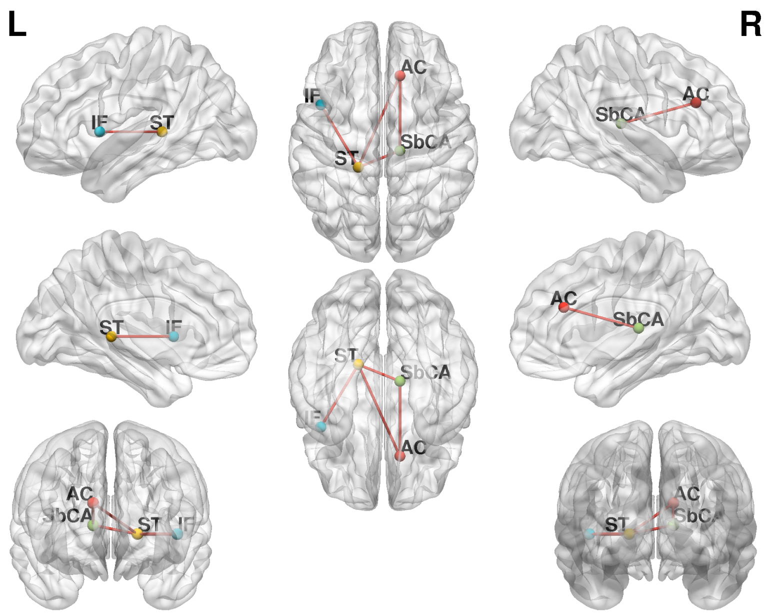


Figure 3.6: Visualization of the brain localization of the effective connection network achieving the highest accuracy discriminating hallucination prone brains considering all the DCM CCF coefficients *per* connection.

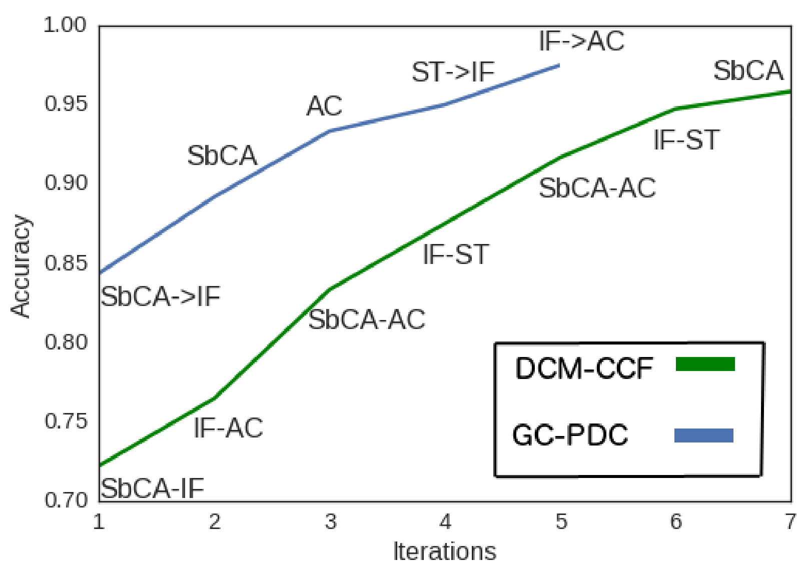


Figure 3.7: LOO cross-validation estimated accuracy at each iteration of the greedy wrapper feature selection process applied to each frequency independently. Labels shown on the plot correspond to the connection added at this iteration. The blue plot corresponds to the results achieved with GC-PDC features, the green plot to the results of using DCM-CCF features.

Table 3.1: Detailed values of the greedy frequency connection selection procedure. Each row corresponds a step in the procedure (#it). Columns correspond to the effective connection (conn.) and the selected frequency of the added coefficient (Hz), and LOO cross-validation average accuracy ± one standard deviation (acc.). Each row corresponds to an iteration where the efficient connection coefficient at the specified frequency is added to the network structure. The GC-PDC connection features are directed (denoted by ->), while the DCM-CCF connection are undirected.

	DCM - CCF			GC - PDC		
#it	conn.	Hz	acc.	conn.	Hz	acc.
1	SbCA-IF	0.10	0.72 ± 0.08	SbCA->IF	0.01	0.84 ± 0.03
2	IF-AC	0.10	0.76 ± 0.04	SbCA	0.01	0.89 ± 0.03
3	SbCA-AC	0.10	0.83 ± 0.05	AC	0.01	0.93 ± 0.04
4	IF-ST	0.01	0.87 ± 0.04	ST->IF	0.01	0.95 ± 0.01
5	SbCA-AC	0.11	0.91 ± 0.05	IF->AC	0.10	0.97 ± 0.03
6	IF-ST	0.09	0.94 ± 0.07			
7	SbCA	0.09	0.95 ± 0.07			

the results achieved by the SVM classifier with GC-PDC features are better than the ones achieved with DCM-CCF features, though they eventually reach accuracy results near 95%. The selected connections have a strong significance i.e. $p<0.0001$ if the random classifier success is modeled by a binomial distribution with 0.5 success probability in a single trial [116]. Table 3.1 reports the detailed values of the greedy selection process at each iteration, including the specific frequency of the efficient connection coefficient added at each iteration.

3.5 Discussion

When I consider each effective connection as a whole, I find that the SVM classifer achieves better accuracy over DCM features than GC features, up to 80% accuracy of a network of effective connection wich is very similar to the most widely accepted AH generative mechanism[156] interactions between areas involving top-down and bottom-up processes. Greedy selection of effective connection frequency coefficients achieves better cross-validation accuracy results, and much more sparse models, which also are in agreement with the theoretical AH generative mechanism, using either DCM or GC features. The results, therefore, support the top-down/bottom-up explanation of the AH generation.

3.5.1 Connection selection.

Effective connectivity analysis by DCM on fMRI data [40] and EEG data[39] shows that top-down inhibition is impaired in schizophrenia patients, which may account for the high prevalence of AH in schizophrenic patients, but is also an additional confounder in our analysis. Contrary to analysis of the relation of the resting networks, such as the default mode network (DMN) to other regions of the brain [8, 11], I can evaluate the significance of connections on the basis of their related accuracy results. Inspection of Figure 3.4 allows to recognize the SbCA-IF connection importance, which points to the memory and emotion driving the recognition in the language areas of signals coming from the auditory cortex as a salient cause for AH. However, there is a contradiction between DCM and GC based results regarding the connection ST-IF. For GC features, this connection is the most discriminant, whilst for DCM features it is uninformative. If we focus on the network with highest accuracy results (the complete network minus the AC-IF connection for DCM features), I may posit that the self recognition in AC plays a lesser role in the AH prone brain than the bottom up process, or that it is compensated by the influence of the subcortical areas (i.e. hippocampus and talamus). However, if we consider the most influential area, we find that the network of AC connections (bottom left in Figure 3.4(a)) achieves the highest accuracy suggesting that self monitoring is the single factor with greatest effect in AH generation, as the masterkey of the AH mechanism[103]. There are three networks which have almost equivalent results (0.80 accuracy), pointing to some redundancy in the generative mechanism supporting alternative explanations[76].

3.5.2 Greedy selection of frequency connection coeffients.

In the greedy selection of connection coefficients reported in Figure 3.6 and Table 3.1, both DCM and GC features lead to the selection of the SbCA-IF connection. The GC-PDC directed connection SbCA -> IF at very low frequency provides very high accuracy, implying that memory, lack of inhibition, and emotional content activating the language recognition are the stronger connection in the functional generative mechanism [9]. The GC self-connection of SbCA and AC at very low frequencies are the next most discriminant feastures, hinting to the importance of the top-down mechanisms of self-awareness and inhibition. Next relevant GC coefficients are the activation of the language areas from the auditory cortex ST -> IF, and the activation of the self-awareness from the language areas IF -> AC corresponding to the bottom up paths of the generating mechanism. The DCM features lead to the same connection selection with different frequencies, with the addition of the SbCA-AC connection, which reinforces the top-down mechanism. I note that GC coeffiencts are selected at much lower frequencies than DCM coefficients.

3.6 Conclusions

Auditory hallucinations have a high prevalence both in healthy and neurologically diseased populations. It is a paradoxical phenomena whose understanding may bring further understanding of the brain mechanisms [9]. Hypotheses about AH generation mechanisms have been validated by cognitive tests, but studies increasingly include neuroimaging data to provide additional empirical confirmation to support them[8], so that new avenues for quantitative research are widely open. In this work I have applied DCM and GC computation methods to rs-fMRI data to obtain measurements of effective connectivity between brain areas that have been identified by previous research as discriminant between Schizophrenia patients with and without a history of AH[135]. In the approach followed, the selected effective connection network significance is measured by the average prediction accuracy achieved by a linear SVM classifier in a cross-validation process.

Chapter 4

Pediatric Therapeutic Social Robotics

In this Chapter I describe my works on the use of assistive social robots in pediatric therapeutics. Section 4.1 gives an introductory setting. Section 4.2 reviews the state of the art of the resources used in this work. Section 4.3 discusses interactive storytelling systems. Section 4.4 discusses narrative generation. Section 4.5 presents the designs worked out for actual experinces. Section 4.6 describes the actual field work carried out with children under the supervision of their tutors. Section 4.7 contains some observations over the experiences. Section 4.8 provides some conclusions that will be complemented in Chapter 6.

4.1 Introduction

Storytelling has been a privileged way of transmitting ideas and knowledge since the very beginning of human civilizations. It has proven to be an engaging way of teaching complex concepts [146, 166, 123, 122, 113], as well as a way to support the development of a wide spectrum of cognitive functions and ski lls in children [58], and even a therapeutic tool for a variety of behavioural disorders [149, 112, 120, 31]. Furthermore, the interactive creation of stories has been a topic of great interest in psychology and games [151], because it is an entertaining activity as well as therapeutic, since it helps the actors to express themselves in a safe imaginary environment where they can face risks and failure without real consequences.

A particular case of this therapeutic use is children in hospital seetings. The rates of incidence of childhood cancer are globally increasing, as well as the survival rates [86, 99]. This means a longer stay in the hospital for those children, which implies a disruption in the social activities both in the family and in the school. Those stays suppose a major stressor and give a general overall feeling of isolation, particularly in children being physically isolated because of low immunity [102].

To improve this situation and reach to these children, the social robots are a good option as a social mediator. Those robots have provided a reliable communication tool in different occasions ([124, 127, 78]), and contrive a lower level of infection risk for the patient than another human or an animal pet.

It must be noted that in this chapter I am not presenting results of a series of experiments but instead I am presenting some preliminary observations from the activities carried out during the early development of the presented model. These activities have been carried out under the supervisionof the children tutors and caring staff, who held the appropriate permisions. In the ensuing paragraphs, I will provide of a series of basic definitions.

4.1.1 Dialogue systems

The development of dialogue systems it's been a topic of remarkable interest since the very beginning of the Artificial Intelligence [142]. This spread of the dialogue systems is linked to the development of a wide range of data-driven machine learning methods have been shown to be effective for natural language processing [130] including the tremendous success for large vocabulary continuous speech recognition of Deep Neural Networks (DNNs), such as Convolutional Neural Networks (CNNs) and Long-Short Term Memory Recurrent Neural Networks (LSTMs) [128].

Traditionaly, dialogue systems have been divided in two separated groups, as seen in Figure 4.1: goal-driven systems, such as technical support services, and goal-free systems, such as language learning tools or computer game characters [131]. At this point, however, it seems that a link between the two approaches can be achieved, where the task-oriented dialogue systems provide a more natural interaction leaving room for small talk and task-free dialogue. In the same fashion, latest improvements open the door for more complex areas to be approached with this dialogue systems such as therapeutic systems and robot interfaces [35].

Recent deep learning approaches leave behind hand-crafted features that represented the state and action space.They require either a large annotated task-specific corpus or a large number of human subjects willing to interact with the yet unfinished system [131]. This makes its development expensive and time-consuming to deploy, and also limits its usage to a narrow domain.

4.1.1.1 Task oriented dialogue systems

Task oriented systems, such as technical support services, and goal-free systems, such as language learning tools or computer game characters [131]. There has

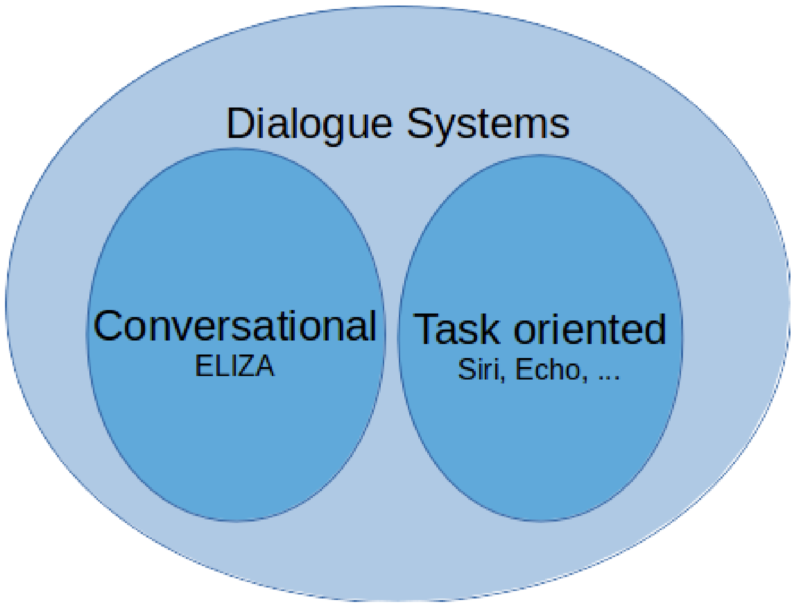


Figure 4.1: Dialogue Systems domain

been a long journey since the first conversational system, ELIZA, considered one of the most important chatbot dialog systems in the history of the field [85], to the task-oriented personal assistants that are currently present in most cellphones or home controlers i.e: Siri, Cortana, Alexa, Google Now/Home, etc. where the system needs to understand a request from the user and complete the related task within a limited number of dialogue turns. They are typically designed according to a structured ontology (or a database schema), which defines the domain that the system can talk about[143]. Getting the info is usually achieved using slot-filling, where a dialogue state is a set of slots to be filled during dialogue [19]. However, this system is inherently hard to transfer to new domains as all features and slots that might be needed are manually encoded [19].

Task oriented systems have beneficed less of the end-to-end architecture and Machine Learning approaches, which do not make assumptions over the domain or dialogue state structure [19], because those methods cast the dialogue problem into one of supervised learning, predicting the distribution over possible next utterances given knowledge of the discourse so far. The supervised learning framework does not account for the intrinsic planning problem that underlies dialogue, i.e. the sequential decision making process, which makes dialogue consistent over time [142].

4.1.1.2 Conversational dialogue systems

Conversational aka open dialogue systems try to produce meaningful and coherent responses in the framework of a dialogue history. They have applications ranging from technical support services, to language learning and entertainment, such as playing games with robots [35]. Approaches to build conversational architectures fall into two classes: rule-based systems and corpus-based systems [85]. The rule based systems correspond to the early attempts. such as the famous ELIZA system, where rules were hand crafted following some *a priori* hints about the desired behaviour of the system. On the other hand, corpus-based approaches learn the system structure and parameters from the data in the corpus, making strong use of machine learning and other learning approaches, mining human-to-human conversations, or the human responses extracted from human-machine conversations [85]. Either rule-based or corpus-based chatbots tend to do very little modelling of the conversational context. Instead they tend to focus on generating a single response turn that is appropriate given the user's immediately previous utterance. For this reason they are often called response generation systems [85]. Given the lack of precise goals, the conversational systems can be formulated as sequence-to-sequence transductors (SEQ2SEQ). However the SEQ2SEQ models tend to generate generic responses, which closes the conversation, or become stuck in an infinite loop of repetitive responses [96].

In the last years conversational systems have integrated the generation power of the current deep learning techniques with great results [128] as they have drawn inspiration from the use of neural networks in natural language modelling and machine translation tasks [131]. The most recent computational models used to build the conversational systems are generative models, such as the hierarchical recurrent encoder-decoder (HRED) [131, 132], a kind of Recurrent Neural Networks (RNN) modelling the posterior of the next word in the sequence from the past context by using two contexts, that of the past words and that of the queries performed by the user. The encoder RNN maps each utterance to an utterance vector modelling the hidden state at both contexts, while the decoder RNN models the probability distribution of the utterances conditional to the hidden state. Utterance generation is achieved sampling the posterior probability density.

4.1.2 Storytelling

Human beings are storytellers. It is human nature to make meaning of our lives by organizing what happens to us into stories. We live our stories as if they were true. We tell stories to understand what happens to us and provide us with a framework to shape our new experiences [80]. Therapeutic storytelling [114] is used with children to achieve two main goals; the first goal is to teach values, the second goal is to improve resilience [90, 141, 98] .

4.1.2.1 Storytelling as a tool to teach values

Storytelling has been used by religions since the beginning of time in all civilizations, as a way of teaching values, morals, etc. Stories have been used as a way to teach people how to behave correctly, how to act [147]. That is, the main codes of social conduct to be followed have been transmitted to us through stories, as well as the consequences that we will suffer from not doing so. It is a very powerful tool, as well as dangerous, since when used incorrectly, it can perpetuate negative values, but if used correctly, it will enhance positive values, thus creating personal growth and community improvement [44].

Storytelling and story book reading is widely used in the school system, both in the early childhood stage and in the primary education stage [44]. In this educational context, the teacher reads a story to the students. This is usually a story where the main character faces an adverse situation, makes right or wrong decisions, and learns a moral from this situation. Depending on the age of the students, the teacher may open a debate, so that the content worked on the story sinks in her students, and make sure that they internalize them correctly and share different points of view. These stories are used to develop values such as generosity, empathy, solidarity, equality, etc [147].

4.1.2.2 Storytelling as a methodology to improve resilience

Storytelling contributes to the emotional well-being of children because every good narrative has a character that solves a problem by taking strategic action, a character they can relate to [59]. Engagement in activities such as oral traditions, storytelling, and talking circles can result in changes of perspective. Thinking about the story to tell, puts kids in control because planification means to put our ideas and experiences in order. Storytelling offers children adaptive strategies to face challenges and build a sense of hope by examining the past [98]. Storytelling can be a way of helping children explore emotions that are too difficult to understand.

Narratives buffer risk as kids explore identities and retrieve a sense of wholeness after experiencing loss or trauma. Storytelling helps children by temporarily avoiding their reality, in order to look at their grief, explore their emotions, and focus on their strengths [115]. Children are interested in sharing their stories because they mean something to them. The importance of this process lies in the evolution of going from victim to controlling your story and understanding it in depth. These are the types of work that interest us, since this is the objective of our work, for the child to develop and improve his resilience through building and sharing their story [141].

4.1.3 Social robots as educational technology

When we talk about educational technology, we usually refer to devices such as tablets, computers, etc. since these are the technological tools that are mostly presented in the field of education and childhood [44]. The interest on the use of robots in social and therapeutic areas has increased in the last years [47, 21, 38]. This is because they provide of a number of proven benefits, specially for children in situation of vulnerability and / or who have been exposed to trauma, as children percive the robot as a peer relate to them, making it less scary, relatable, and more approachable [14] [59]. In the same way, they are more readily accepted than a human by ASD children [13] and enhance the learning time and quality of children with potential symptoms of a developmental disability [81]. These complex cognitive technologies are proving to be useful mediators for individuals that need an adaptation to the world [41].

The main reason why robotics can be a good complement to storytelling is that robots allow us to make the whole process of storytelling interactive. That is, a switch is made from a scenario where the teacher tells a story and the child listens to it, to another scenario where the child builds her/his own story, along with the robot [90]. Once the story is created, they listen to it together. The subject goes from a passive process to an interactive one, making the child the focal point of the socio-educational intervention [14].

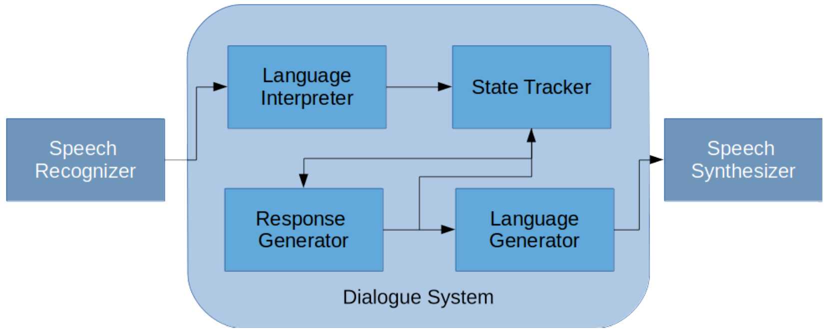


Figure 4.2: Traditional dialogue System

4.2 State of the art

As previously stated, the topic of interactive storytelling as been largely ignored and thus, the literature that can be found is, at best, tangencial. However the literature around the dialogue systems is more prolific and modern. In this section I present the traditional architecture of dialogue systems as well as an overview of the literature so the presented work can be placed in a solid ground.

4.2.1 Architectures of dialogue systems

The traditional architecture for dialogue systems illustrated in Figure 4.2 includes a series of system modules, each with specific functionality [130]:

- Speech Recognizer, in charge of providing the lexical units for the system extracting them from the voice signal,
- Language Interpreter, in charge of extracting meaning from the stream of lexical units by Natural Language Processing techniques,
- State Tracker, in charge of modelling the dialogue state and dynamics, it keeps track of the goal in task oriented systems and of the contextual information in task-free systems.

- Response Generator, produces the semantically grounded response to the current input,
- Language Generator, formulates the response in correct language constructs by Natural Language Generation techniques, and
- Speech Synthesizer generates a recognizable voice signal for the communication with the human side.

Obviously, the Speech Recognizer and Speech Synthesizer modules have meaning in voice-based dialogue systems. Text based dialogue systems do not need them. Each of these modules can be tackled with as an independent problem, hence they have been approached using different techniques. This variety is evident in the list of examples in Table 4.1.

Speech Recognition advances due the renewed interest in Artificial Neural Networks are exemplified by [69], or the review in [18]. Deep Neural Networks have been also influential in Language Interpretation [109] and Response Generation [96, 132, 97]. State tracking has been addressed from many sides with a variety of techniques [73].

4.2.1.1 End-to-end dialogue systems

In recent years the so-called end-to-end dialogue system architectures have become popular and so, some modules, or even all of them, have been collapsed into a unique module of Response Generator, as illustrated in Figure 4.3. Those systems, mostly based on neural networks, have shown promising results on several dialogue tasks [130]. The main difference between the classical approach and the end-to-end approach is the emphasis on data driven system construction. While the classical approach is much hand crafted and introduces a priori assumptions and design restrictions in all the modules, via specific computational models, the end-to-end approach assumes that the whole architecture can be induced

Table 4.1: Description of systems in the literature

Reference	Description
[132]	Developing a Hierarchical Encoder-Decoder Model
[131]	End-To-End dialogue Systems generated by Hierarchical Neural Networks
[69]	Speech Recognition with Deep Recurrent Neural Networks
[97]	Adversarial Learning for Neural dialogue Generation
[73]	Review of Machine Learning for dialogue State Tracking
[96]	Deep Reinforcement Learning for dialogue Generation
[160]	A Network-based End-to-End Trainable Task-oriented dialogue System
[144]	Speeding up adaptation of Spoken dialogue Systems by Recurrent Neural Networks shaping rewards
[163]	An Entropy Minimization Framework for Goal-Driven dialogue Management
[142]	End-to-end optimization of goal-driven and visually grounded dialogue systems
[19]	Learning End-to-End Goal-Oriented dialogue
[109]	Deep Sentence Embedding Using Long Short-Term Memory Networks: Analysis and Application to Information Retrieval
[34]	Deep Reinforcement Learning based Dialogue System
[137]	Adaptation of Spoken dialogue Systems using RL
[143]	On-line adaptation of Spoken dialogue Systems using Active Reward Learning

Table 4.2: Main features of referenced works. EM Entropy Maximization, DRL Deep Reinforcement Learning, MN Memory Networks, RL Reinforcement Learning, CNN Convolutional Neural Network, LSTM Long Short Term Memory, RNN Recurrent Neural Network, DRNN Deep Recurrent Neural Network, HRNN Hierarchical Neural Network.

Reference	System type	Task-oriented?	Architecture	Module	Method
[132]	SEQ2SEQ	No	End-to-end	Dialogue Generation	HRNN
[131]	SEQ2SEQ	No	End-to-end	Dialogue Generation	HRNN
[69]	-	-	End-to-end	Speech Recognition	DRNN
[97]	SEQ2SEQ	No	End-to-end	Response Generation	RL
[73]	review	-	Traditional	State Tracking	ALL
[96]	SEQ2SEQ	No	End-to-end	Dialogue Generation	RL
[160]	SEQ2SEQ	Yes	End-to-end	Dialogue Generation	NN
[144]		Yes	Traditional	Evaluation	SLTM
[163]	Inf. Retr.	Yes	Traditional	Response Generation	EM
[142]	-	Yes	End-to-end	Dialogue Generation	DRL
[19]	-	Yes	End-to-end	Dialogue Generation	MN
[109]	-	-	Traditional	Language Interpreter	RNN with STLM
[34]	-	No	Traditional	Response Generation	DRL
[137]	-	Yes	Traditional	State Tracking	RL
[143]	SEQ2SEQ	Yes	-	Evaluation	RL

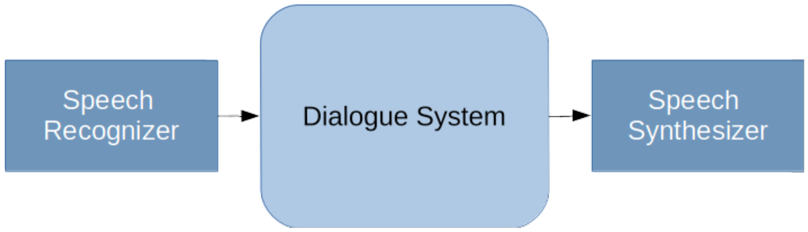


Figure 4.3: End-to-end dialogue System [109]

from the data via learning algorithms [20, 19]. This shift has been possible because of the success of Deep Learning Neural Network approaches [66]. There are two main categories of end-to-end dialogue approaches [130], on one hand those that search in a dataset of fixed possible responses, and on the other hand those that select the utterance that maximizes the posterior distribution over all possible utterances. The second approach allows more dynamic responses, as the response generation can be decomposed to the word level.

4.3 A Proposal for an Interactive Storytelling Model

What I propose is the creation of storytelling systems that fall in the intersection between the narrative creation, social robots, dialogue systems and therapeutic systems as illustrated in Figure 4.4, i.e. the interaction and narrative creation provide a feedback loop, lead by a possible therapeutic objective and embodied in a robot system to provide a more natural experience, with the softest learning curve possible.

In this context the idea is to use the generative power of the latest Deep Learning techniques, that have already provide good results in vocabulary and speech related tasks [128] for fuelling the creative aspects of the storytelling, i.e. the generation and adaptation of the plot. However, from the Dialogue Systems

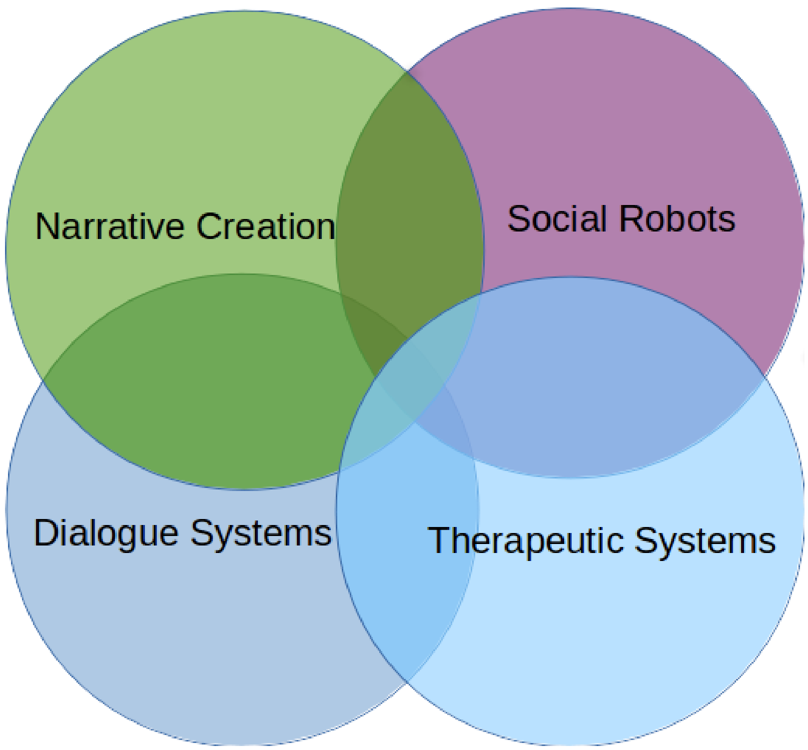


Figure 4.4: Diagram of Storytelling Systems

approach, this implies a more goal-oriented dialogue as an story provides an intrinsic planning problem. In fact, a story can defined by a sequential decision making process and thus, require a consistency in the dialogue over time, which the supervised learning framework does not account of [142].

Furthermore, interactive storytelling systems would be ideally embodied in a robot with a social objective, as this provides that the storytelling can take place in any familiar environment for the children, reducing possible rejection. Also those robots are suggested to provide with a grater enjoyment in the interaction with children [51]. This two are important factors when considering the use of this systems for more complex applications as therapy or special education.

The following are needed components of an interactive storytelling system, which can be embodied in a social anthropomorphic robot:

- Language generation from semantic representations, which can involve also speech synthesis for natural spoken interaction. Commercial robots, such as Nao, already have good speech synthesis resources.

- A semantic representation of the story plot, that may allow to generate alternative paths, and that can be generatively manipulated using some kind of "plot operators". Plot generation may be driven by some kind of popularity or audience engagement measure, so it becomes some kind of optimization problem that can be solved by stochastic search.

- A capability to asses the state of plot knowledge by the audience. An engaged audience may be able to show its engagement by answering simple questions about the plot. Thus, the robotic storyteller may check them and decide which is the best point for story restart, or it may generate alternative plot lines that provide the required knowledge. This is a process alike to student modelling in automated e-learning systems.

- Capability to sense audience engagement. For instance, obtaining the pose of the head it would be possible to decide if the audience is still attentive to the story, or they have lost interest. Audio cues may help additionally. Noisy ambience is likely the indication of a lost audience. However, the robot must also be able to detect questioning relative to the story, which is a high indicator of attention and engagement.
- Capability to answer questions about the story, and to reschedule/reorganize the story as a consequence.

All these components require specific research efforts, some of them concurrent with research in other areas, such as task oriented dialogue systems, or some tutoring systems for people training.

4.3.1 Proposed embodiment in the NAO robot

However, in this first model the process, as seen in 4.5, starts with the robot's presentation where it refers to itself and the features it has in an informal an childlike manner. Then the focus is redirected to the actual dialogue process of the NAO robot with simple questions and answer (i.e how old are you?) and small talk. This dialogue is from where the rest of behaviours are called, via a switch in the robots OS, NAOqi's, focus. This implies the need to monitor when this focus is released, which elicits a memory event that triggers the previous dialogue, bypassing the presentation. This way of processing implies that the robot has no long term memory of the interactions, and only a short term memory inside the dialogue. The behaviours that can be launched from the dialogue are the two stories described in 4.5.1 and 4.5.2, small animations to entertain the kids from the robots animation's library (i.e. air guitar playing), and a more lengthy animation with sound of a Tai Chi performance.

The stories are developed with a animation tagged text and a number of sto-

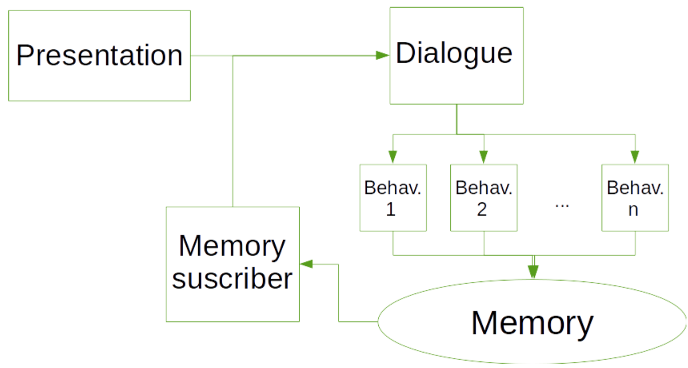


Figure 4.5: Scheme of the application with representation of focus switches

rytelling characteristics, as the objective is, not only to verbalize the story but to "tell a tale" implying a multisensory input for the receiver that transform the process to a social comunication [41]. The flow of the history is altered using pauses to resemble a human storyteller in order to break the possible monotone rhythm of the robot. Also, each character is characterized by a personal voice, created using the changes in pitch and speed of the robot's speech, and a colour in the robot's eyes. This way the children are able to detect differences associated to characters, as is usual in the traditional storytelling.

4.4 Narrative generation models

The problem of narrative plot creation is a very distinct topic, as it has a close relationship with natural language and dialogue but some closed rules that do not apply to normal speech. The plot is the driver of the most narrative forms in the Western culture [106] and is usually defined by initial situation, conflict and resolution. However, for the plot to be successful, and applauded as such by the audience, it must have coherence and character believability [121]. At this moment, it is not a widely researched topic, although there have been practical works as the one presented in [60], where a repository of existing stories are used to provide with the skeleton of new plots that match a given user query, or even theoretical approaches to the idea of end-to-end system capable of extracting narrative models from text and use those to generate new narratives [151].

In this previous stages the used stories have been selected and handcrafted, however to achieve the intended therapeutic goals I decided that traditional folktales where there is a clear hero, antagonist, and trial are the best option as they have been histoically used to teach values and problem resolution. This oriented the research towards folktales structures as the monomith or "hero's journey" presented by Campbell[24] and the morphology by Vladimir Propp [118]. In the same fashion, the corpus made of folktales ProppLearner [1] explained in [48] is a tool that has been already considered.

4.5 First interaction design

The aim of the preliminary work is to assess the effect of the storytelling in the children and take some first reactions to the interaction with the robot in a number of different settings. For that the robot performed in four different situations: a children's hospital, a school group age 10-11, a Bulgarian school group age 5-7, and a Bulgarian daycare, with two different stories.

In order to make the experience more whole and provide the children with a sense of anticipation and a way of remembrance I created additional material: a video of the robot telling the story with puppets[2] that was shown to the school group age 10-11, a colouring book with the characters provided to the childrens in the hospital, and an Instagram account [3] to make the robot more relatable.

[1] https://dspace.mit.edu/handle/1721.1/100054?show=full
[2] https://www.youtube.com/watch?v=19bTQ9mXlDM
[3] https://www.instagram.com/endorbcig

4.5.1 First story - Peter and the wolf

The first implemented story is the one of Peter and the wolf is a traditional and widely known story for the children to whom it was oriented. It has a length of 2 minutes and is designed for younger children, with a message of not telling lies not particularly linked to the considered children's situation. However, I decided, due to simplicity and the familiar nature of the story that it was a ideal first contact story. It consist in four characters with three different voices and I provided two personalized animations to accompany the text, the call of Peter and the laughter. Its very structure is too simple to translate to Propp's morphology as there is no "hero's journey".

4.5.2 Second story - Fearless John

In this case, the story is also a generally known story, at least in the non-Bulgarian setting. The length of the performance is of 8 minutes and is oriented to more grown ups. In this case the story was selected specifically because of the message it provides, as it narrates the adventures of a fearless hero and the way he faces it in a nonchalant way. I considered a proper message for children that found themselves in a situation of high stress and fear.

Following Propp's mophology the story of Fearless john can be defined as follows:

$$\alpha B^3 C \uparrow D^1 E^1 W_0^0 K^2$$

where α is the initial setup, with the hero lacking fear, B^3 is the decision of going to find it, $C \uparrow$ the action of leaving his parents house, D^1 the task given by the Queen, E^1 the completion of said task, W_0^0 the wedding with the princess and K^2 the finding of the fear thanks to the princes.

The dramatization of the story, has nine characters with five voices, and I included sound effects for the monsters and one personalized animation. For the activities performed in Bulgaria the system was changed due to the lack of Bulgarian text-to-speech. The text was replaced by recordings of a female human voice reading the story and the dialogue launch could not be used, therefore, a manual launch of the behaviours was implemented.

4.6 Activities

4.6.1 Children's hospital

I realized two different trips to the hospital in differentiated dates with no overlap in the group of children of each date. The NAO robot was included as part of a more extensive activity, with two other robot types, two Parrot's jumping sumos[4] and two Sony's[5] AIBO robot dogs, as seen in Figure 4.6. The age range in the general group was 4-14 and the rooms in which I performed were not segregated by age. The groups varied from 1 to 6 children per performance as I went from room to room in different hospital areas, from isolated children to daycare. The sessions conditions in both trips where similar, with no previous information provided to the children and a duration of 15-30 minutes in each setting before moving to the next room. The performance consisted in putting the robot on, giving the additional colouring book and paints, a small presentation, and free interaction. If the interaction did not naturally occur I questioned about what they wanted the robot to do and encouraged siblings and caregivers to join.

[4]https://www.parrot.com/global/minidrones/parrot-jumping-sumo
[5]https://www.sony.com/

Figure 4.6: Parrot's jumping sumo (left) and Sony's AIBO (right)

4.6.2 School group age 10-11

I realized a single working session in a local school to interact with a group of children, age 10-11, that had previous contact with the research group and, particularly, playing with small robots and drones. In this case there was an introductory class session featuring the projection of the video of the Fearless John story told by the NAO robot. As in the previous situation, I included the NAO robot in a more extensive activity interacting with small drones and two AIBO robots. I divided the 30 children in 5 groups of 6 children and rotate activities every 15 minutes as seen in Figure 4.7. This way one group of children interacted with the NAO robot, while another two groups were playing each one with one AIBO robot, and the last two groups were playing with the drones. There was no directed insructions on how to develop the robot-children interaction, thus it evolved spontaneously. The idea was to give the children the opportunity to interact with kind of robots regardless of preference in order for them to provide opinion in the different options based in interaction and not solely appearance or first impressions.

4.6.3 School group age 5-7

I also realized a single session in a Bulgarian school, with children ages 5-7. The children were divided in two groups depending on age, one of 5-6 years olds and

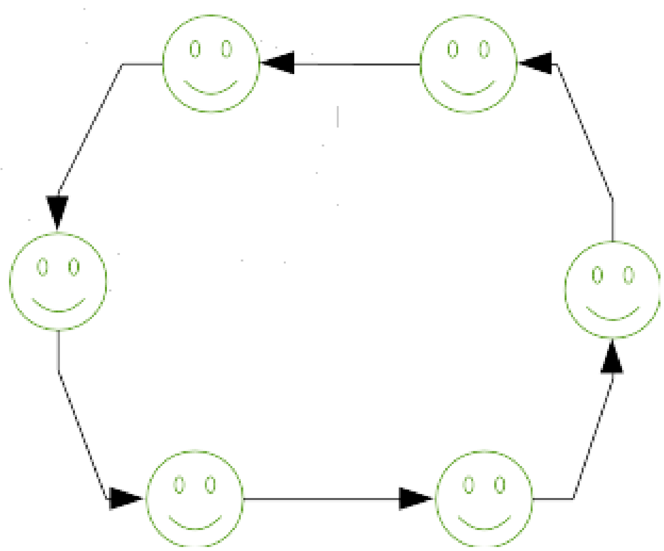


Figure 4.7: Rotative setting

other of 6-7 year olds. Each one of the groups interacted with the NAO robot in a 30 minutes session, that were made equal in all conditions. As shown in Figure 4.8 the children sit around the robot, at a safe distance. The robot was presented and they were explained that it is programmable. Then they sang a song with NAO, listened to the Fearless John story, the robot performed the Tai Chi animation, and finally they were invited in groups to touch it and play with it for a short while and voice their questions.

4.6.4 Daycare

I performed a single session in a daycare centre in Bulgaria with a group of special needs children, as presented in Figure 4.9. The children where of different age, autonomy level, and cognitive disorder type. In this case most children were accompanied in close proximity by parents or caregivers at every moment. The session lasted 45 minutes, and consisted in a first get in touch with the robot, singing a familiar song and dancing with the children twice, telling the story of

Figure 4.8: Children listening to the robot

Fearless John, and performing the Tai Chi animation twice. Then the children where encouraged to touch and get near the robot, with assistance when needed.

4.7 Observations

The children reactions where significantly more negative in the hospital setting than in any other of the situations. In this context the younger the child the more negative reactions toward the NAO robot were displayed, which did not occur with the AIBOs. Even the more grow up children reacted in a significantly neutral manner, when it was enthusiastically received in the rest of the sessions carried out in schools or daycare centers.

Regarding the interaction intent, there was high interest in verbal and physical interaction in the school and daycare settings with the children spontaneously speaking to the robot or reaching to touch the hands and feet. In the hospital, however, the attempts to interact where generally weak and most often guided by the lead of a caretaker with a significant amount of children accepting or

Figure 4.9: Children prepearing for the robot's performance

witnessing the action. Although, it is to notice that the feedback received from caregivers was positive which could imply the need of a different measurement of enjoyment in such situations.

Focusing in the verbal interaction, the interest was high but brief as the children lost interest fast when the robot failed to recognize some words. This failure was more accentuated due to the enthusiasm of the children that speaked to the robot in a fast, loud, and collective manner, with a number of questions and phrases shouted at the same time.

The most significant observation, however, was the unexpected interest in the robot's actual storytelling from the school group age 10-11. As previously stated these children have already seen the story in a video online. I got asked if the robot was the same as the one they saw and they requested to see it "live". I run the story and during the first 1-2 minutes of the story all the other groups left the more interactive (drones), and other social (AIBOs) options to sit in front of the robot. Even when the teacher tried to interrupt to allow them to have free play time she was silenced in order to keep hearing the story.

4.8 Discussion and conclusions

I am interested in the robot-child communication in a context of emotional or psychological need. Our approach is to use the storytelling as a tool to interact with the child in a non-stressful and secure yet meaningful way. More precisely, I am very interested in the possibility of giving these children psychological tools to better manage possible stressful situation using a fun and non threatening tool. The storytelling has been historically used with this same objective. In this work I provide some observations that show that hospitalized children are in need of a more proactive actor for a successful interaction, as there is a significant ignorance of the robot, which comes in tune with the ignorance of others listed as effect of major stressor in [102]. However, a more indirect approach might be necesary, as an agressive start might maximize the negative first reactions reported in this work. Also, the verbal interactions proved to be too rudimentary in this preliminary stage for the children's free-play, however, there was a good response to non verbal communication in all the groups. On other note, the hard rejection of the robot could be linked to traces of emotional regression which is a common consecuence of a major stressor in children [102]. It will be useful to improve the complexity of the system, and to extend the dialogue and variety of options in order to improve the communication between child and robot.

Chapter 5

Opinion propagation models

This Chapter deals with Agent-based spatial dynamic modeling of opinion propagation. Section 5.1 provides introductory remarks to the study. Section 5.2 introduces the notation and the basic simulation of the eco-social model that is the basis for all further experimental works. Section 5.3 gives the detailed description of each of the eco-social interaction models that have been developed and experimented with along this study. Section 5.4 gives the details of the simulations carried out to explore the behavior of the proposed alternative systems. Section 5.5 reports the results of the computational experiments. Section 5.6 gives some conclusions that will be complemented in Chapter 6.

5.1 Introduction

I focus on the approach of [84] which studies the spatial interaction of agents with their neighbors and the effect of several opinion change policies. Essentially, the model is a cellular automata model, which has the inconvenience of having fixed spatial relations. Nevertheless, the model achieved to reproduce interesting effects of the sociological models proposed of the interaction between majority and minority opinions. Following this lead, I narrow our problem to the particular issue of how to impede or delay the emergence of social system with a monolithic opinion situation, i.e. a homogeneous distribution of agent opinions, which is a problem similar to the prevention of infection spread covering the entire population, as presented in [82], if we match "infection" with the opinion being majority from the beginning, and that the "infected" agents are both curable and not vaccined. Contrary to [84] which poses the problem in a static spatial scenario, I endow the agents with the ability to move in a virtual space, so that their spatial relations allow their opinions to interact. Moreover I consider the existence of influence relations among agents, and some kind of charisma property that gives weight to the influence when forcing the change of opinions of other agents.

I am interested in the interplay between ecological and social dynamics, to answer questions in a wide spectrum of disciplines, ranging from historical misteries such as the Khemer early cities [45] to the dynamics of human population migration [94, 77], and actual technological problems such as the migration of processes between processors in high performance computing [7, 64] and energy aware computing [36]. Most ecological modeling (e.g. recent studies of predator-prey-subsidy spatial dynamics [134]) deals with the motion of the agents in the pursue of food, or escaping predators, whithout much consideration to coherent forces inside agent communities. On the other hand, we are witnessing daily that strong social forces drive the human populations sometimes overcoming the basic survival forces that would give higher priority to the satisfaction of basic necesities. I am interested in including social mechanism in the dynamics of agents in order to achieve models for such kind of behaviors. Therefore I include a social graph as the backbone of the agent population. Forces arising from the friendship graph are competing with survival forces emerging from the agent-environment interaction in order to drive the agent decisions to move in a virtual area.

5.2 The eco-social model

I propose a general model that encompases the ecological constraint of the search for resources (food), and the social constraints of opinion sharing, friendship and solidarity mechanism of sharing resources between friends (family). I model the social constraints through an underlying friendship graph relating members of a community/family. This graph modulates decisions about opinion and resource sharing, as well as spatial motion. Agents move towards family members sharing the same opinions, and trying to maximize their social esteem. Also agents move towards food repositories or to friend agents willing to share resources. I give detailed equations in the next section, and I have developed implementations for the realization of computational experiments aiming to discover the behaviors emerging from the variations around the base model. I provide experimental simulation results that show some unexpected effects, such as the collapse of big communities. I consider that the proposed model is a first step towards an improved understanding of the interactions between ecological and social strata of the human societies.

We have a collection of N agents $A = \{a_i\}_{i=1}^{N}$, and M resource repositories, i.e. food sources. At time t, each agent a_i is characterized by spatial position in a virtual discrete space $P_i\left(t\right) \in \mathbb{N}^2$, an opinion $o_i\left(t\right) \in [0, 1]$, a hunger level $h_i\left(t\right) \in [0, 1]$ increasing by 0.01 after each iteration, and a social esteem level $s_i\left(t\right) \in [0, 1]$. The perception of each agent is limited to a circle of radius $\theta\left(t\right)$ around its actual position in virtual space. Agent's spatial behavior is driven by the need to satisfy hunger and to increase its social esteem. Attending to both drivers simultaneuysly can lead the agent to contradictory decisions, or can reinforce each other. Friendship graph $G(t) = (A_t, E_t, W_t)$ determines the food sharing relations between agents. Edges between friends have weights that determine the strength of friendship, so that the edge disappears when its weight becomes zero. Agents will be more prone to share food the higher the friendship level, and seek them in case of hunger, but after a period of spatial closeness agents can accept new agents into their friendship relations, or remove friendships after a period being out of touch. Each agent recognizes the following relevant subsets of the collective of agents:

- Local neighbors, $\{L_i(t) \subseteq A\}_{i=1}^N$, which are agents that are perceived by the agent at time t because they lie in a position inside a spatial circle of radius θ^L around the agent: $L_i(t) = \left\{a_j \left| \|P_i(t) - P_j(t)\| < \theta^L \right.\right\}$. The agent determines its motion in space according to the hunger/social esteem, making it more attracted to friends or agents with opinion proximity regarding more need of food or social esteem.

- The set of friends $\{F_i(t) \subseteq A\}_{i=1}^N$, which is the set of agents linked with a_i through the friendship graph. That is: $F_i(t) = \{a_j \,| \exists (a_i, a_j) \in E_t\}$.

These sets are defined at the start of the simulation, according to the spatial distribution of the agents, as will be explained below. Besides, each agent a_i has the following attributes:

- Aggressiveness ag_i, defined as the agent's "motivation" to influence neighboring agents. The aggressiveness value is bounded $c \in (-1, 1)$, considering 0.9 the highest level of aggressiveness and -0.9 the lowest level. Agent's aggressiveness is set initially in the simulation at the time of agent creation, and does not change along the simulation.

- Resources r_i, defined as the agent's food buffer. This buffer is set initially in the simulation at the time of agent creation with a value bounded

$r \in (-1, 1)$, and is filled when the agent finds a resource's patch or emptied as the resources are being used. The propensity of the agent to share this resources with friends depend on the fullness of this buffer and level of hunger.

Our simulation proceeds as follows:

1. Initially, the agents are randomly placed in the virtual arena at positions $P_i(0)$, their opinion o_i, aggressiveness ag_i, and resources r_i are generated by random sampling from a uniform distribution. Moreover, at time 0:

   (a) I create the group of local neighbors, $L_i(0)$, as the nearest neighbors of each agent inside the perception radius θ in this initial spatial configuration.

   (b) I create the initial friendship graph as the local neighbors at time 0, something like defining the families of agents at birth,

   $$E_0 = \{(a_i, a_j) \,|\, \|P_i(0) - P_j(0)\| < \theta\},$$

   Each created edge has initial weight $w_{ij}(0) = 0.5$.

2. Simulation is carried out in discrete time steps. At each time instant t the agent attributes, i.e. position, opinion, hunger, social esteem, and friends are recomputed according to the following rules:

   (a) The agent considers changing its opinion in each iteration. The new opinion can be higher or lower in the gradation of $[0, 1]$, where we can consider 0 and 1 as the "radical" opinions. This influence is related to the influential neighbors' aggressiveness and it's effectiveness depends on the influenced agents' social esteem as follows:

$$o_i(t+1) = (1 - s_i)\left(\left\{\frac{\sum_{j\in I_i} a_j o_j}{\sum_{j\in I_i} a_j}\right\} - o_i(t)\right), \tag{5.1}$$

This way the agent is more prone to bend to the influencers' opinion the lower it's social esteem is.

(b) The agent motion equation is as follows:

$$P_i\left(t+1\right) = P_i\left(t\right) + \triangle_t\left(P_i\left(t\right), L_i\left(t\right), F_i\left(t\right)\right), \tag{5.2}$$

where the spatial displacement is the result of the hunger and social esteem driving forces:

$$2n\triangle_t\left(P_i, L_i, F_i\right) = h_i * \left(\sum_{k\in L_i\cap F_i} w_{ij}\left(P_k - P_i\right)\right) + (1 - s_i)\left(\sum_{k\in L_i}\left(1 - \left(|o_j - o_i|\right)\right) * \left(P_k - P_i\right)\right), \tag{5.3}$$

The first term of eq. 5.4 represents the attraction to the friends, and the second the attraction to agents with similar opinion. However, in case of not having any agent inside the preception radius the equation changes as follows:

$$\triangle_t\left(P_i, L_i, F_i\right) = h_i * \left(P_\rho - P_i\right), \tag{5.4}$$

Where P_ρ is the position of nearest resource repository inside the perception radius. In case of not having any resource repository in sight the movement is toward a random direction.

(c) The weights in the friendship graph are updated as follows:

i. For existing friendship links $w_{ij}\left(t\right) > 0$, we have $w_{ij}\left(t+1\right) = w_{ij}\left(t\right) - 0.1$ if $a_j \notin L_i\left(t\right)$, otherwise $w_{ij}\left(t+1\right) = w_{ij}\left(t\right) + 0.1$.

ii. If $w_{ij}(t+1) <= 0$ then the link disappears from the friendship graph and the agent from the set of friends, i.e. $E_{t+1} = E_t - \{(a_i, a_j)\}$ and $F_i(t+1) = F_i(t) - \{a_j\}$.

iii. If an agent is close to a non friend agent, then friendship is started with a small weight value. Formally, if $a_j \notin F_i(t) \& a_j \in L_i(t)$ then $w_{ij}(t+1) = 0.1$, $E_{t+1} = E_t \cup \{(a_i, a_j)\}$ and $F_i(t+1) = F_i(t) \cup \{a_j\}$.

iv. If the link's weight surpasses the value of 1 it is automatically reduced to 1.

(d) The social esteem is degraded or increased in relation with the proximity of the agent's opinion to that of its local neighbours, as follows:

$$s_i(t+1) = g - \left(2g * \frac{\sum_{k \in L_i} |o_j - o_i|}{n}\right) \tag{5.5}$$

where g is the maximun gain, or loss as it is simetrical. In our experimentation g is set as 0.2. In case of $n = 0$ the social esteems decreases 0.2.

(e) If an agent is near one or more friendly agents the probability that this agent gives resource units to the agent with less of them is:

$$p = 1 - (w_{ij} * (h_i - h_j)). \tag{5.6}$$

Agents always share the same amount of resource units, which is 0.1, that is reduced from a_i's resources buffer and added to a_i.

(f) If there are a number of agents near a resource repository a random agent receives as many resource units as needed to fill it's buffer as long as the resource's repository has that many resource units left. If not the case, the agent receives as many resource units as the repository can provide.

(g) Resources increase in each repository with a value of 0.1 each iteration with a top limit of 1 resources per source.

(h) If hunger is above 0.6, then the agent consumes 0.1 units of its food resources if possible. In case hunger value surpasses 1 the agent is considered dead and removed from the simulation.

3. Simulation stops when the time limit is reached or there are no agents left in the context.

Departing from this simplistic model I elaborate a hierarchy of dynamical systems which are planned to simulate increasingly complex agent interactions regarding opinion change and its relation to spatial distribution of the agents. In each model the agents are randomly placed in the virtual arena at positions $P_i(0)$, and the simulation is carried out in discrete time steps following a series of rules.

The rules define the way the agent identifies the local neighbors and the influential neighbors, and are updated from model to model as well as more detail is added to agents perception and inner logic, creating more significant differences between them, in order to achieve a bigger variety of behaviors which resembles better real life situations.

5.3 System models

In this Section I provide explanation and formal specification of the behaviors of the agents in a series of increasingly complex systems. The appendix of the Thesis contains the flow diagrams speicifying the behavior of the agents in each kind of system.

5.3.1 System 1: Simple Gregarious System

The logic of the agent in the simple gregarious system is as follows: I consider the local neighbours group, L_i, as the n nearest neighbors of each agent and the influential neighbors group, I_i, all the agents inside a radius from the influenced agent, i.e $a_j \subseteq I_i \leftrightarrow \|P_i\,(t) - P_j(t)\| < \theta$. The agent itself has a simple gregarious behavior, moving towards the spatial point with more agents inside its local neighbors group, according to the following equation

$$P_i\,(t+1) = P_i\,(t) + \Delta(P_i, P_{L_i}), \tag{5.7}$$

where $P_{L_i}$are the positions of the agents in the local neighbours group, and $\triangle(P_i, P_{L_i})$ computes the motion vector in the next step takeing into account the agent position and the postions of the local neighbours as follows:

$$\triangle(P_i, P_{L_i}) = P_i - \frac{\sum_{k\in L_i} P_k}{n}, \tag{5.8}$$

Regarding its opinion, the agent considers the opinions influence as the number of agents with that opinion in the influential neighbors group, without taking into account its own opinion. As represented bellow:

$$\triangle(p_i, P_{I_i}, O_{I_i}) = \left\{ \frac{\left\{ \left| I_{i_{o_j=o_k}} \right| \right\}_{j=1}^{|I_i|}}{|I_i|} \right\}_{k=1}^{|O|}, \tag{5.9}$$

Then, a random selection is performed with the probabilites obtained in the previous ecuation to determine the new o_i agent's opinion.

This model is the most contrary to the flousihing of opinion diversity, it can be expected that the minority opinions would disappear more rapidly in it.

5.3.2 System 2: Simple Peer Seeker System

The next complexity level in the hierarchy of systems is given by a peer seeker agent behavior represented in Figure A.2 of the Appendix. Here I alter the local neighbors selector of system 1. This time, instead of being attracted to the n nearest agents there are only considered the agents of the same opinion changing the function of the previous system as follows,

$$\triangle(o_i, P_i, P_{L_i}, O_{L_i}) = P_i - \frac{\sum_{k \in L_i} P_{k_{o_k = o_i}}}{n}, \tag{5.10}$$

It can be expected that this system will be more tolerant to opinion variety as each agent would look for opinion peers in nearby spatial positions, reducing the possibility of getting too strong influence from a single opinion.

5.3.3 System 3: Ally/Enemy System

Next complexity step is the ability of the agent to consider its neighbors as enemies or allies. In this system, whose algorithm can be found in Figure A.3 of the Appendix, I harden the behavior present in the previous one. Although local neighbors are selected in the same way this time neighbors with different opinions are not only ignored but actively avoided. Changeing the position updateing ecuation as follows

$$\triangle(o_i, P_i, P_{L_i}, O_{L_i}) = \left(P_i - \frac{\sum_{k \in L_i} P_{k_{o_k = o_i}}}{n}\right) - \left(P_i - \frac{\sum_{k \in L_i} P_{k_{o_k \neq o_i}}}{n}\right), \tag{5.11}$$

In this model the agents tries to protect it's opinion from other opinions influence, looking for “its own” groups composed of allied agents.

System 4: Ally/Enemy Randomized System

This system, represented in Figure A.4 of the Appendix, is very similar to the previous one adding a random component to the heading of each agent, so the spatial behavior have a more natural non deterministic component. The function results as follows,

$$\triangle(o_i, P_i, P_{L_i}, O_{L_i}) = \left(P_i - \frac{\sum_{k\in L_i} P_{k_{o_k=o_i}}}{n}\right) - \left(P_i - \frac{\sum_{k\in L_i} P_{k_{o_k\neq o_i}}}{n}\right) + \eta, \tag{5.12}$$

where η is a random component that adds a deviation of a variable number of degrees in any of both directions, from 0 to 180.

The random component of the agent behavior models all kind of noise that may happen when the agent is making its decisions or obstacles that may appear while carrying them. Also, an opinion-delay is added to make for the agent possible to walk up to 10 steps before considering the influences. This way, I force a certain change in neighbours from influenciation to influenciation.

5.3.4 System 5: Ally/Enemy Randomized System with Charismatic Agents

In the fifth system I depart from the previous system by introducing additional complexity in the agents' definition, introducing the idea of agent's charisma (its ability to influence others). It's algorithm can be found in Figure A.5 of the Appendix. This alters the previously used ecuation por opinions' probability to the following,

$$\triangle(p_i, P_{I_i}, O_{I_i}, C_{I_i}) = \left\{\frac{\sum_{j\in I_i} c_{j_{o_j=o_k}}}{|I_i|}\right\}_{k=1}^{|O|}, \tag{5.13}$$

In this context an agent with a negative charisma value would have a negative influence, making it less probable for its opinion to be selected by the influenced agent. The resulting system is expected to be significantly less prone to early homogeneity.

System 6: Ally/Enemy Randomized System with Charismatic/Stubborn Agents

This system, whose algorithm can be found Figure A.6, counteracts to the charisma introduced in the previous system with a resistance parameter in the influenced agent, its stubbornness. I define the stubbornness of the agent as its reluctance to change opinion. This resistance is set in the setup of the agent as $r_i \in [0, 1)$, and is included in the ecuations as a new added probability, forcing $\triangle(p_i, P_{I_i}, O_{I_i}, C_{I_i})$ to cover only the $(1 - r_i)$ that rest. It is obvious that an agent with a resistance of value 0 would be equal to the agents from the previous system.

5.3.5 System 7: Ally/Enemy Randomized System with Conservative Agents

To improve the previous agent and attempting to make it more real life like, I consider a dynamic resistance $r_i(t)$ to change opinion. This mean that in each iteration the stubbornness of the agent is decreased in case the opinion is changed and increased by $r_i(t + 1) = r_i(t) + 0.1$ if it is not. Although this can be seen as contrary to what happens in real life, taking account of how, in many cases, it is the new converted which are the most radical, I wanted to present this as some kind of conservative agents with a strong tendency to conserve an opinion they are accustomed to. Therefore, habit increases stubbornness, while frequent change reduces it. In addition I included a charasteristic to the spatial behaviour so the agent regulate the attraction to allies / repulsion to enemys taking account of the distance to the nearest of each group. It's algorithm ccan be found in Figure A.7

5.3.6 System 8: Ally/Enemy Randomized System with Varied Attitude Agents

This system illustrated in Figure A.8, introducing a variety of agent attitudes. This way, instead of considering an identical influence process for all the agents involved I consider the influencing processes based in different measures. In the ones presented some agents would be blind to other agents charisma or number, giving a greater complexity in the opinion change decision making.

5.3.7 System 9: Ally/Enemy Randomized System in Social Networks

Taking from the ally/enemy randomized system I improve the ally/enemy categorization as represented in the Figure A.9. Instead of considering the opinion to qualify another agent as "friendly" or not, I endow the agents with a social graph (created in the very beginning of the simulation or provided as an a priori) substituting the local neighbors in the previous systems. From that moment the local neighbors are those social network connected agents even if they get spatially separated. The system attempts to differentiate the "family" agents from the "strange" agents. This way an agent could be very well connected -the "socialite"- with agents pulling it to different positions, or completely isolated -the "hermit".

5.3.8 System 10: Ally/Enemy Randomized System in Dynamic Social Networks

Based on the previous system, the social network may make the ally/enemy consideration more real. However, a static social network makes little sense when human-like behavior is considered. Therefore I plan to include some memory in the agent so it could remember the nearest neighbors and how much time they have been in the proximity. This way if a previous "family" agent is separated for a long enough time their connection in the social graph would be removed wheres is a "strange" agent is near for a long enough time it could be considered no longer a stranger and a connection between them would be created in the social graph creating more dynamic networks.

Models assume a collection of N agents $A = \{a_i\}_{i=1}^{N}$, each agent a_i is characterized by spatial position in a virtual space $P_i \in \mathbb{R}^2$, and an opinion $o_i \subseteq O$ from a given opinion set $O = \{i\}_i^M$. Each agent identifies two groups:

- Local neighbors, $\{L_i \subseteq A\}_{i=1}^{n}$, neighbors to whom the agent feels attraction/rejection in time to displace its spatial position towards them, and
- Influential neighbors, $\{I_i \subseteq A\}_{i=1}^{k}$, neighbors that affect the agents' opinions change.

5.4 Experimental design

5.4.1 First three systems

I have implemented the models in Netlogo[1] and Repast Simphony [2]. In the first set of experiments, I have programmed the first three systems: the Simple Gregarious System, the Simple Peer Seeker System, and the Ally/Enemy System.

[1] http://ccl.northwestern.edu/netlogo/
[2] https://repast.github.io/repast_simphony.html/

The experimental aim was to observe the general movement of the agents and find the one that facilitates mostly a variety of opinions, conversely delaying or impeding homogeneity. To this end, I explore the reaction in the diversity of the systems to changes in the n value when selecting the n nearest neighbors for the local neighbors selection and changes in the radius value when searching for the influence neighbors selection. In all experiments, I run 10 repetitions of each model with each combination of model parameter values. The size of the population of agents was 200 for computational limits of available resources. The number of resource repositories is $M = 100$ in all simulations, both randomly placed in the simulation arena following an uniform distribution. The arena has a size of 50×50 with bouncing borders. The perception radius values tested were $\theta^L \in \{1, 4, 7, 10, 13, 16, 19, 22, 25\}$, measured in discrete patches that the simulation software grid defines over the continuous arena space. The set of nearest neigbors considered have sizes $\theta^I = \{1, 25, 50, 75, 100, 125, 250\}$. Size of the set of opinions was selected in the set $\{2, 3, 4\}$. For the 4th system and higher, I considered a maximun path deviation degree of 30 or 45 degrees to both sides. I added an opinion delay so the more complex spatial behaviour of the agents had a real impact in the opinion spread, this supposed that an agent moved 10 times for each opinion reconsideration. The first four systems all were clearly prone to converge to a homogeneous opinion situation, therefore I run the models until all the agents have the same opinion and measured how long take them to achieve this homogeneity. However, in the last three systems their behaviors tend to oscilate without an opinion overrunning all the others which forced us to set an stoping parameter based in ticks, setting to 16,000 the maximinun of steps. I observed that the system always reached steady states before this time limit. The meaning of steady state is that opinion distribution remained constant for a long period of time. Two important measures of the system evolution are the number of active friendship links in each iteration, and the number of agents remaining alive. The number of resource units available in the resource repositories, and opinion variability are additional measures of the behaviour of the system.

5.5 Results

5.5.1 Agent trajectories

The results of the simulations are presented in in two ways. One is the plot of the trajectories followed by the agents in a simulation, such as shown in Figure 5.1 for system 1. This visualization is helpful to achieve an understanding of the effect that the initial position of the agents may have on the final distribution of opinions and the changes in spatial behavior when considering changes in the number of neighbors considered. In this figure the path of the agents can be seen as the lines that part from them and changes in opinion are represented by color changes. The visualization is repeated for the Simple Peer Seeker System in Figure 5.2 and the Ally/Enemy System in Figure 5.3.

In those images it can be perceived the significant difference in behavior from the first two systems, the Simple Gregarious System and the Simple Peer Seeker System, to the third Ally/Enemy System. The first two have small difference between them, presenting more compact groups in the Simple Peer Seeker System. In the Ally/Enemy System, however, it can be appreciated a less clear grouping in the agent's spatial behavior and less if not none compact group exists in any final configuration. This mean that as it could be expected, less spatial "vision" in system with just attraction forces, considering "vision" the group of other agents a particular agent can "see", derives in smaller and more isolated groups whereas a wide "vision" supposes bigger compacted groups.

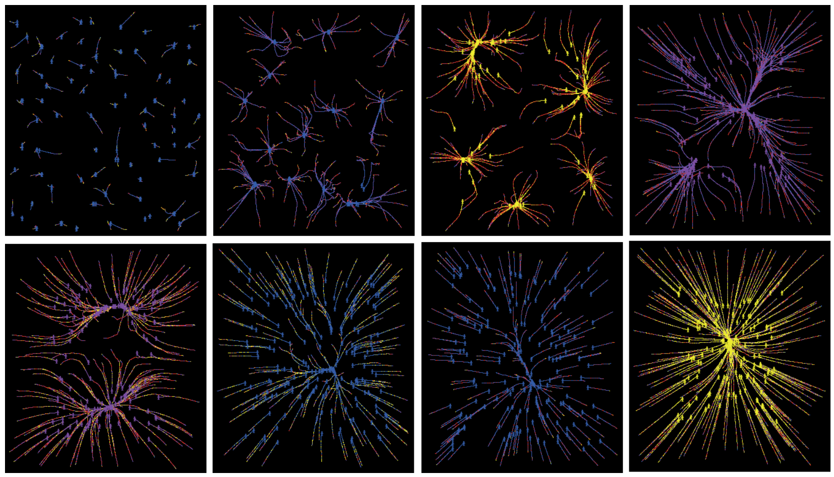


Figure 5.1: Some dynamical evolutions of agents following the specification of System 1.

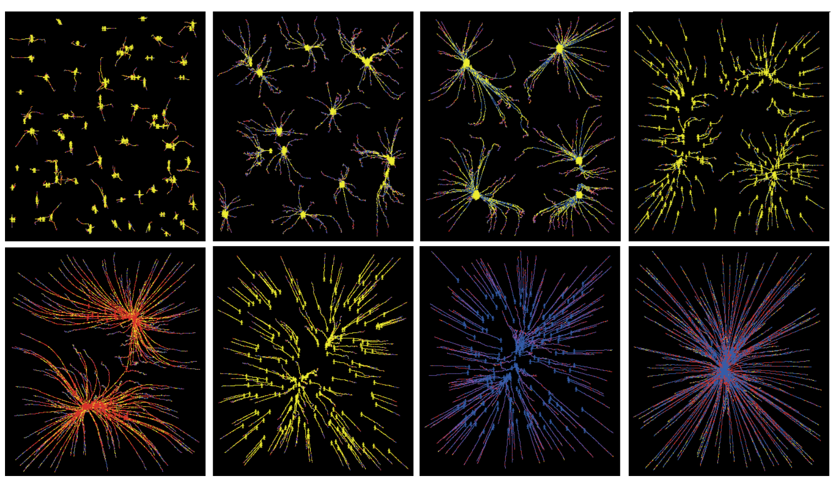


Figure 5.2: Some dynamical evolutions of agents following the specification of System 2.

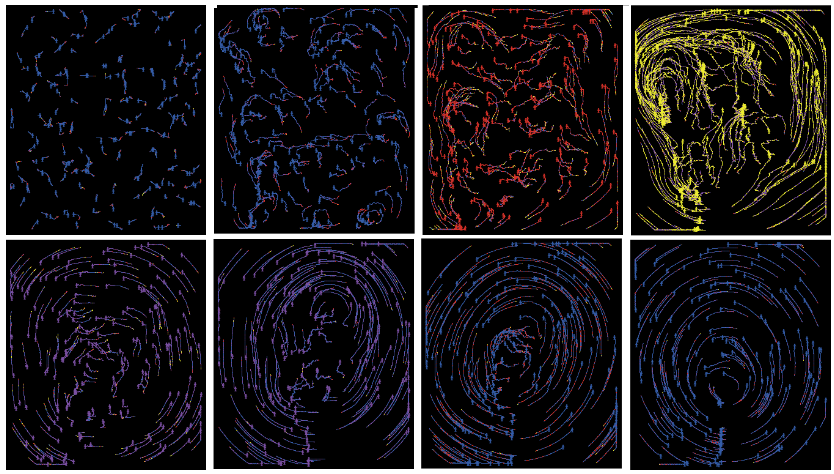


Figure 5.3: Some dynamical evolutions of agents following the specification of System 3.

However, in the system that considers reject forces too, this behavior is changed and wider "vision" supposes even less compacted groups than in the previous configurations, as the agent receives a bigger number of forces that force it to avoid more populated spots.

5.5.2 Evolution of opinion diversity

Another visualization of simulation results are the plots in Figures 5.4, 5.5, and 5.6 that show the mean disappearance time (measured in simulation iteration ticks) of opinion diversity versus both the number of neighbours considered and the influence radius. Regarding this plots we carried out separate simulations for the different opinion variety configuration: with two, three, and four different opinions. The systems react in different ways to changes in both perception parameters. In Figure 5.4 it can be appreciated that there is an evident drop in the diversity endurance in some point. In the results of the System 1, this drop is when the number of neighbours considered is exactly half of the initial population or the considered influence radius is of five patches, what can be

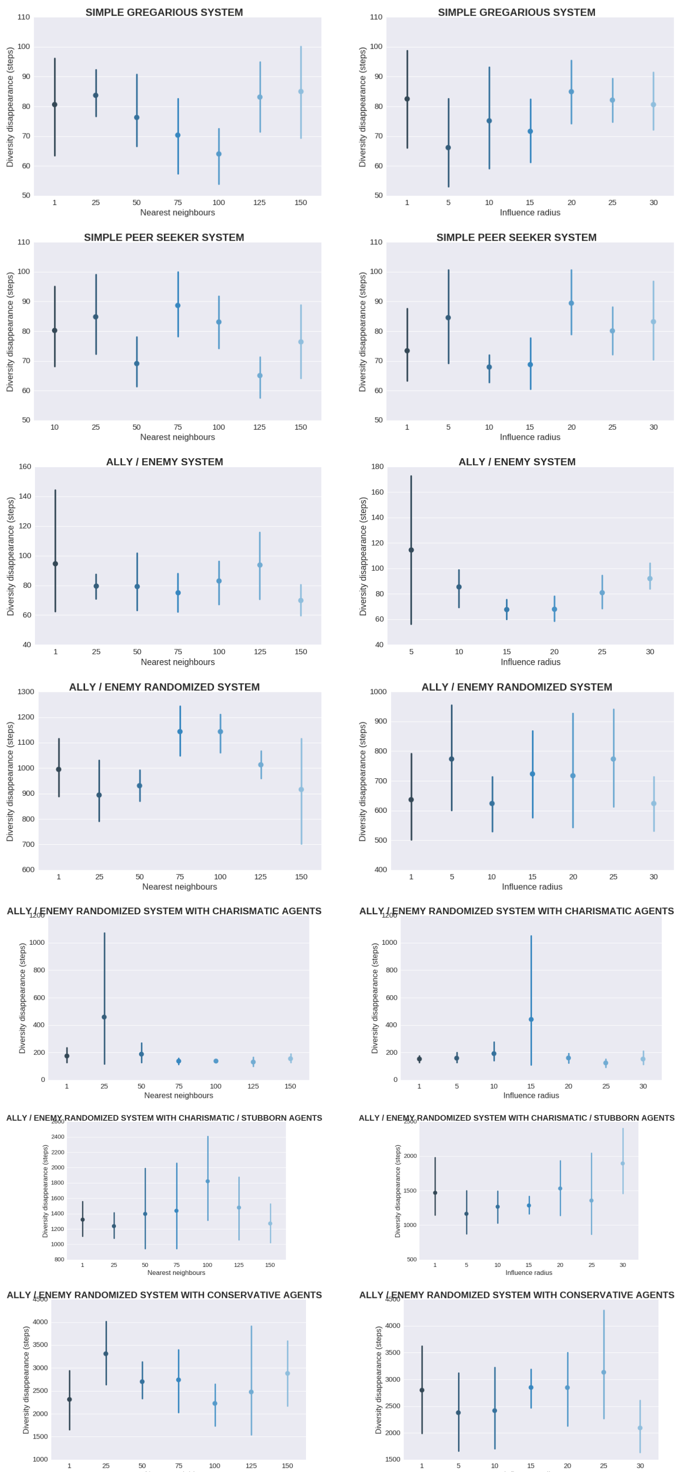


Figure 5.4: The effect of the neirgborhood size (left) and increasing radius (right) in the time to disappearance of the minority opinion, startating with two different opinons.

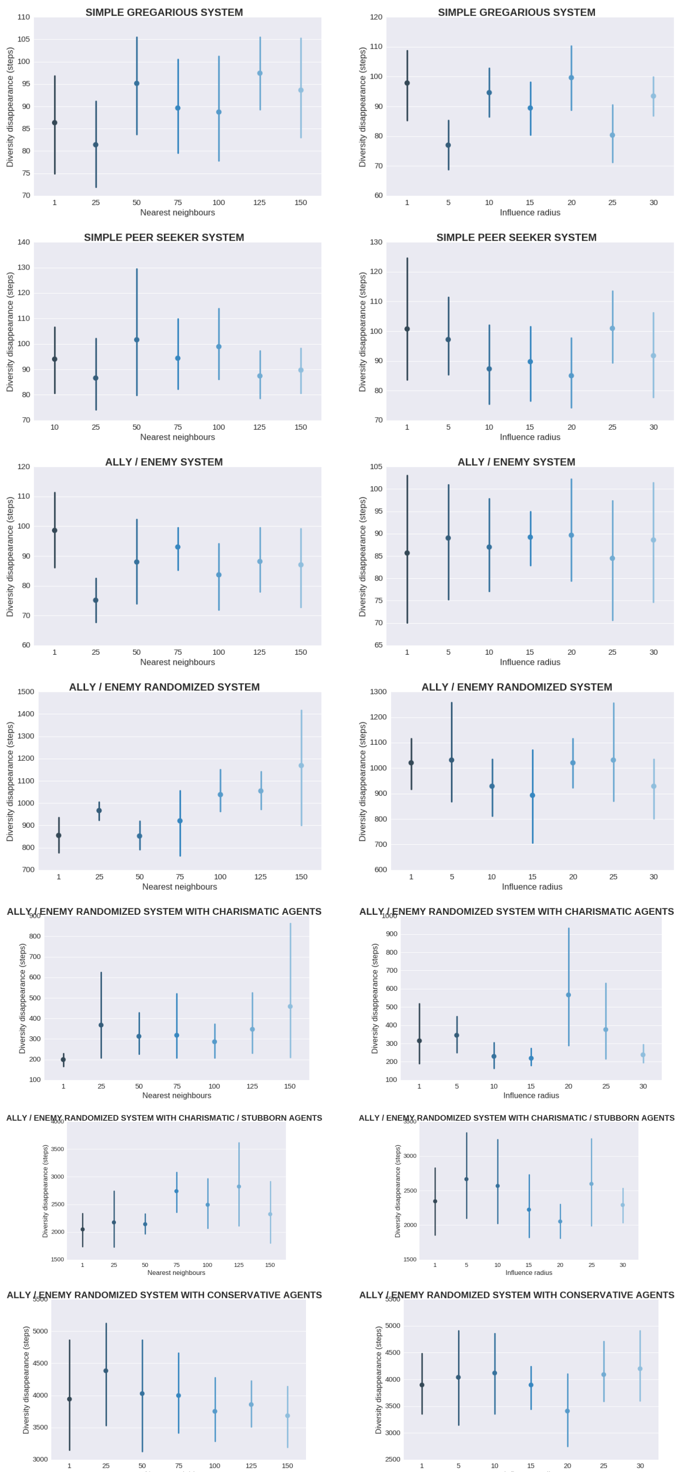


Figure 5.5: The effect of the neirgborhood size (left) and increasing radius (right) in the time to disappearance of the minority opinion, startating with three different opinions (c).

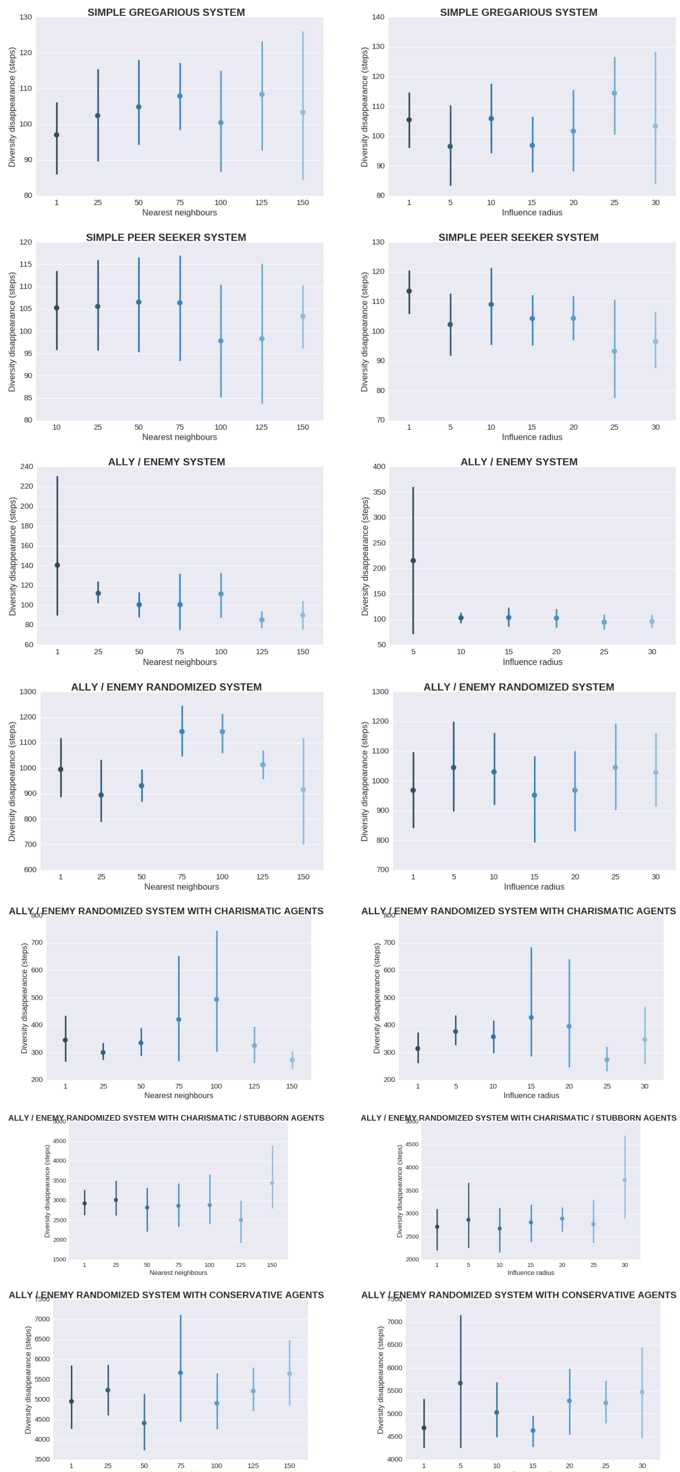


Figure 5.6: The effect of the neirgborhood size (left) and increasing radius (right) in the time to disappearance of the minority opinion, startating with four different opinions.

considered as little. For System 2, there are two significant drops in both of the experiments: when considering the 50 or 125 nearest neighbours and when considering 10 or 15 patches radius. Also, there is a high peak resistance to homogeneity when considered the 25 nearest neighbours, just as in the previous system. The third system has a significantly different behaviour when changes in the number of nearest neighbours are applied.When the changes are applied to the influence radio, however, it shows a drop similar to the one in the first system, when considered a 5 patch radius. In the results of System 4 there are three drops when changing the radius, in 1, 10 and 30 patches considered. When observed the variations of nearest neighbours, however, it shows a downward trend with a slight peak at 50 nearest neighbours considered. For System 5, there is an evident change in behaviour with high peaks both when 15 patches influence radius considered and with 25 nearest neighbours taken into account, the last peak showing a higher endurance similar to the one present in the first two sistems. The System 6 shows a drop in homogeneity resistance when the values in the middle are considered concerning the influence radius and the opposite behaviour when the nearest neighbours are the considered variable. The results of System 7 show a peak in resistance when the 25 nearest neighbours are considered, as occurs for Systems 1, 2, and 5, and a significant drop when 30 patches considered for the influence radius.

The results obtained from the simulations when starting with 3 different opinions are shown in Figure 5.5. The results of System 1 keep a single significant drop, this time when considering the 25 nearest neighbours, seems noticeable that the System 2 shows a drop in the same case as well, while mantaining a second resistance drop when considering the 125 nearest neighbours. In that same context there can be seen a fall in the resistance of the System 3. For the Systems 4 and 5, however, the drop seems to be where just the nearest neighbour is considered, with a peak when the 25 nearest neighbours are considered. The System 4 seems to show a drop where the 50 nearest neighbours considered. When considering the influence radius changes, however, there is less unity in the results, with resistance drops in Systems 1 and 3 when considering a 25 patch radius but a high peak in the same context in the System 2. Also, it can be seen a similar general behaviour in Systems 6 and 7, and significant drops in Systems 4 and 5 when an influence radius of 10 and 15 patches is considered.

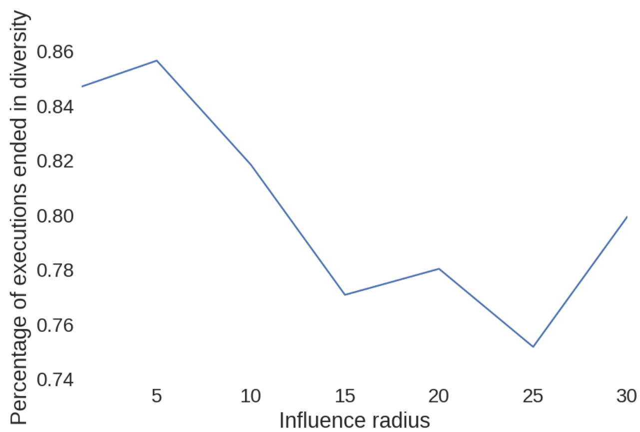
In the last group of simulations, starting with four different opinions, the plots in Figure 5.6 show an slightly more stable behaviour. However, there are visible drops when considering the 100 nearest neighbours in Systems 1 and 2, with a timid peak in the System 3. Also, Systems 2 and 3 show a fall in the resistance when considering the 125 nearest neighbours, while the System 1 shows a peak in the same context. Both systems 4 and 5 show a upward trend in the middle values that abrouptly drops in the last two cases, agains the peaks in the last two systems when considered the 150 nearest neighbours. Regarding the changes in influence radius there are peaks in the Systems 1 and 7 when considering an 25 patch radius, whereas there is a drop in the same case for the System 2. Similarly there is a resemblance in the behaviour in the Systems 1 and 2 for the first few influence radius considered that is contrary to the behaviour in the System 3. In the same fashion, Systems 4 and 7 show a general behaviour opposite to that of the Systems 5 and 6.

Regarding the value ranges, the simulations show higher endurance of opinion diversity in every system with the increasing of the initial number of opinions. From System 4 to 7, however, there is a significant change in said values. While Systems 1,2, and 3 needed around 50-140 steps to achieve opinion homogeneity, the System 4 results vary from 400 steps to 1500. After this point, the systems were prone to oscilation and, thous, we set a stop at 16000 steps if stability was not achieved yet. We could observe that in Systems 5, 6, and 7 only three to six repetitions of each combination of parameter values stopped before the 16000 steps and even in this situation there where significant diferences in scale, even in the simulations of the same model, depending of the number of opinions considered. In the System 5, endowed with charismatic agents, the simulations starting with one or two opinions offered results that where in the 0-200 steps range, except for the situations where the 25 nearest neighbours where considered, where there is a clear peak in the opinion diversity endurance, or a influence radius of 15 patches is considered, where another peak is visible. Regarding simulations with three and four opinions, however, the opininon diversity endurance varied from 100 to 1000 steps, which could be regarded as a wide range. For the System 6, where the resistance to agents' opinion is added, there is a similar jump in endurance scale. While the simulations with two or three opinions stop at 500-2600 steps, the simulations of three and four opinions reach their finish step between 1500-5000. Also, it is to notice that a bigger number of simulations than in the System 5 ended before the 16000 steps limit. In System 7, again, there is a noticeable jump in endurance scale, however, the jump is not located between the one and two opinions' systems and the three and four opinions' system as the systems before, but between the four opinions' system simulations and the rest of them. Here the systems that considered one, two, or three different opinions stopped at steps between 1000-5500, the simulations considering four opinions, however, stopped at steps between 3500-7500. As it can be seen in all cases there seems to be a growing in opinion diversity endurance following the complexity of the considered model, as it could be expected.

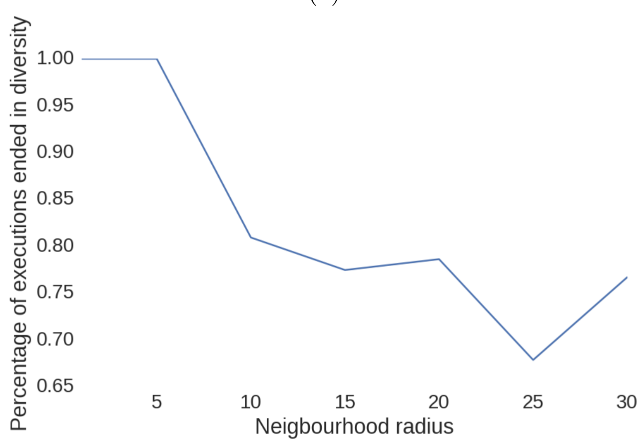
5.5.3 Influence of spatial parameters

The research question "do spatial perception parameters determine the survival of opinions?" is answered by the results in Figure 5.7 where we show the percentage of the simulations that end in a state where more than one opinion is sustained by the agents in the population as a function of the radius of influence (Figure 5.7a) and the radius of of the local neighborhood (Figure 5.7b). Increasing both radii produces a decrease in the number of simulations that end with two or more opinions alive. The effect of the local neighborhood radius is stronger than the influence radius. In Figure 5.7b the percentage decreases from 100% when $\theta^L < 10$ down to 65% when $\theta^L = 25$, while in Figure 5.7b if goes from 85% when $\theta^I = 5$ down to 75% when $\theta^I = 15$. The salient fact is that the spatial perception has a strong effect on the preservation of alternative opinions, we have better preservation when the radius is small so that spatial disconnection leads to more compact communities which may preserve minority opinions.

Regarding the delay in the disappearance of the opinion diversity we can observe in Figure 5.8 that both plots, when considering the values from 10 to 30, reflect a invert behavior with peaks in the values 15 and 10 regarding the neighborhood radius whereas a drop is shown in the same values when the influence radius is considered. It is significant also that there are no fast convergence towards opinion homogeneity in any case, with all the situations considered showing a number of steps slightly above 3000. Regarding the deviation, we can observe that it is wider and more stable during changes in neighborhood radius, in comparison with the values associated to changes in the influence radius, specially when considering 10 and 15 patches.



(a)



(b)

Figure 5.7: The effect of increasing influential (a) and neighborhood (b) radius measured by the percentage of simulation runs ending with more than one opinion alive.

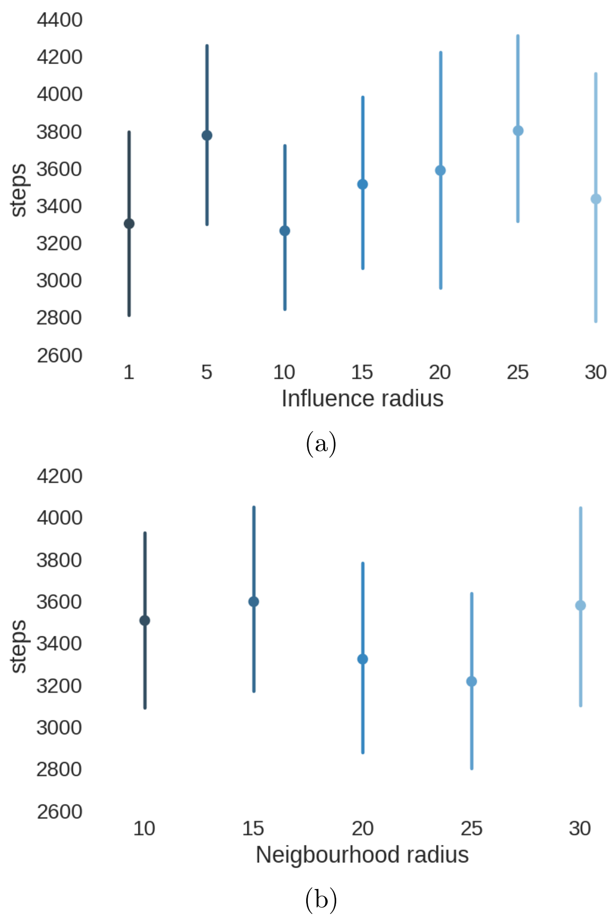


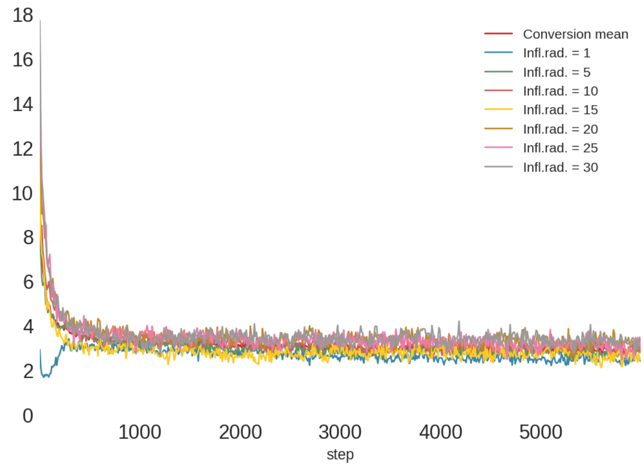
Figure 5.8: The effect of increasing influential (a) and neighborhood (b) radius measured in number of steps needed to the disappearance of opinion diversity, i.e. convergence to a single opinion.

5.5.4 Speed of convergence to single opinion

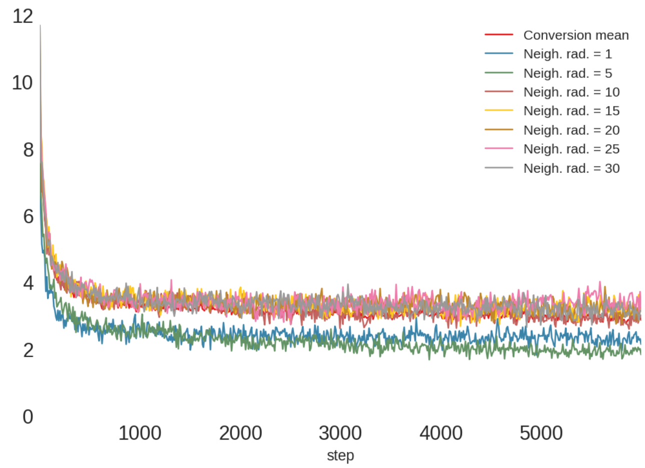
To further assess the speed of convergence, we recorded the number of opinion changes in each step and get the mean to observe the evolution of said number during the simulations. In figure 5.9 the two plots shows a big drop in the first steps to then stabilize in a fairly low number of opinion changes, a tiny percentage of the 200 agents in the population. However is interesting to notice that while when considering changes in influence radius all the cases converge to similar values. When considering changes in neighborhood radius (Figure 5.9b) there are two clearly separated groups: the first, formed by the cases where the neighborhood radius is 1 or 5, that shows a number of opinion changes around 2.5, and the second, formed by all the other cases, that shows a similar trend to the first group although with a number of opinion changes around 3.5.

Focusing in the drop of number of opinion changes that occurs in the first steps in figure 5.10 we can observe that, regarding the plot of changes in influence radius, the number of changes in the very first steps seems linked to the size of the radius, which can be expected. However is interesting to notice the gap between the evolution of radius 1 and 5 in the first 250, and 15 and 20 in the first 200 steps to then converge in similar values. It is specially notorious the evolution of the case where the influence radius considers a unique patch as is the only case when the number of opinion changes rises during the first steps to the same values as the other cases. When focused in the plot regarding changes in neighborhood radius we can observe a gap between the two smallest radius and the rest of the cases. However, unlike the previous plot, the two groups maintain a constant gap between them with a similar stabilization point near step 150.

In order to find significant relationships between the two radius we considered the data grouped by said differences in contrast to changes in one or other of



(a)



(b)

Figure 5.9: Evolution of number of opinion changes in groups as a response to the increasing influential (a) and neighborhood (b) radius.

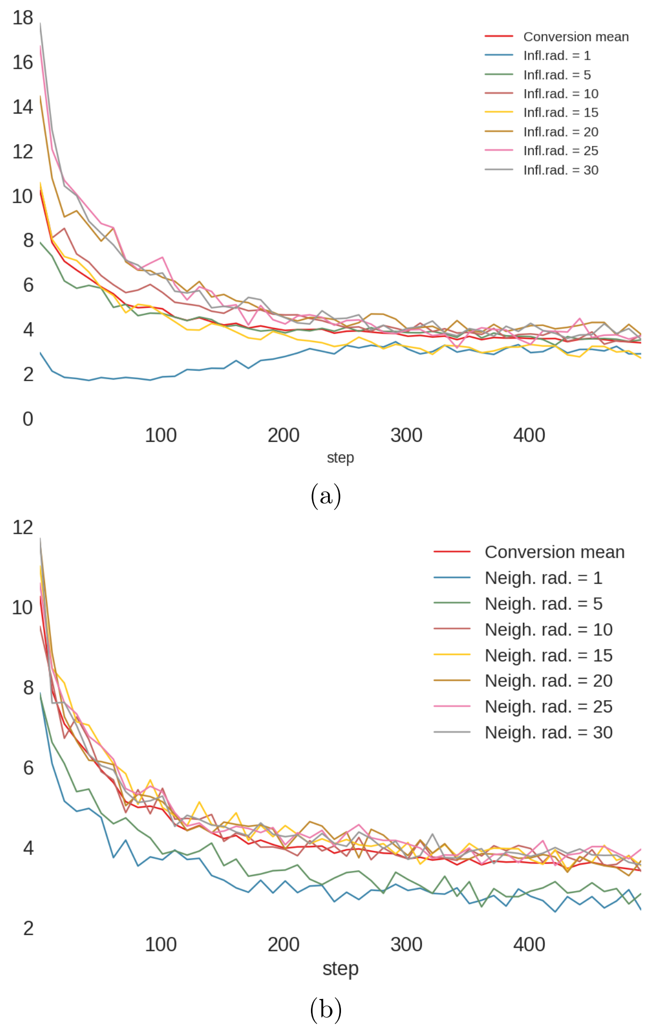


Figure 5.10: Evolution of number of opinion changes in groups regarding influential (a) and neighborhood (b) radius in the first 500 steps.

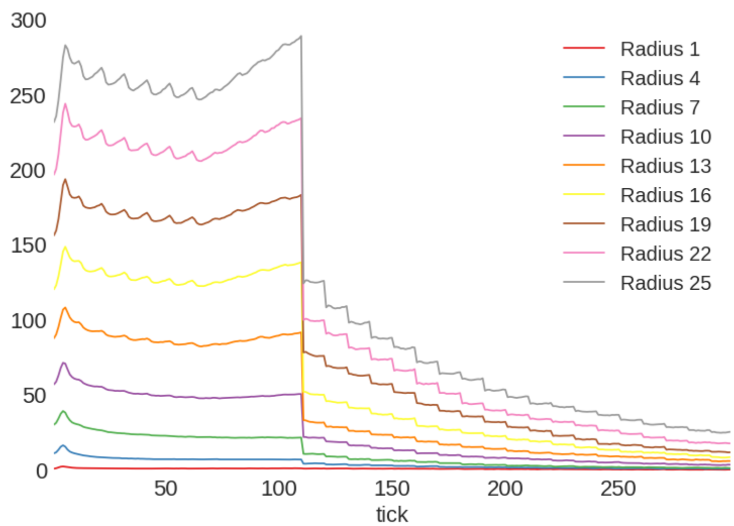


Figure 5.11: Evolution of number of links.

the radius. As we observe in fig 5.9 the cases where the influence radius and the neighborhood radius are equal converge to a lower number of opinion changes, even if it starts with a number similar to the total mean of opinion changes. Following with the first steps of each case, the data shows that when the influence radius is smaller then the neighborhood radius it converges faster than any other case, which seems to go along the lines that the wider neighborhood radius helps a faster opinion group creation.

5.5.5 Influence of perception on the survival of communities

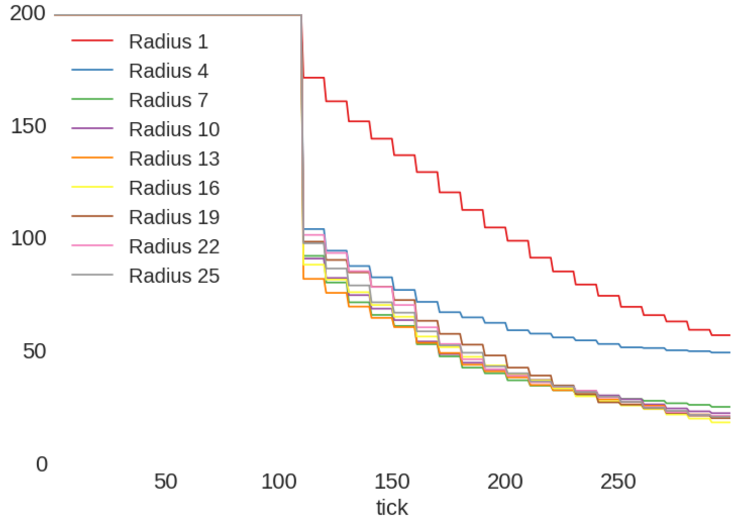


Figure 5.12: Evolution of agent population.

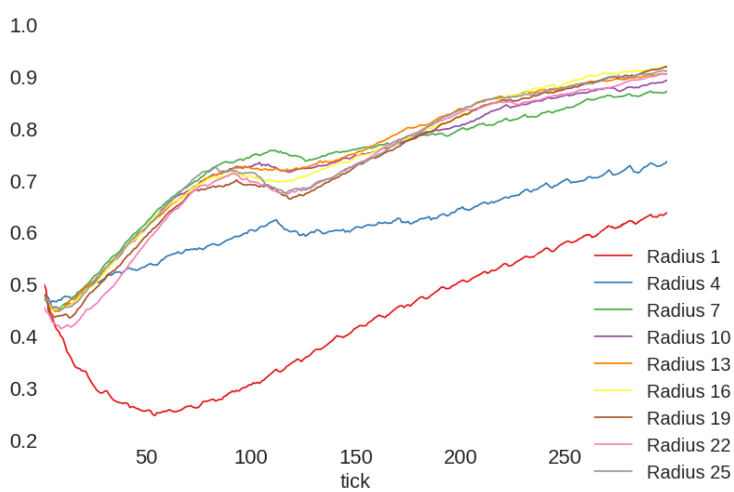


Figure 5.13: Evolution of average resource quantity.

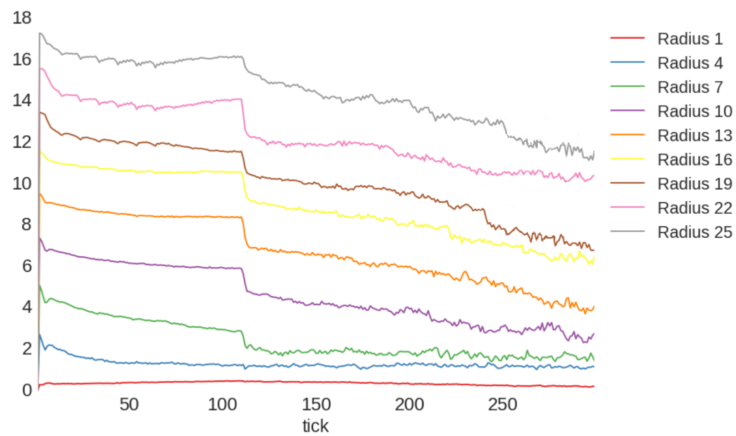


Figure 5.14: Evolution of spatial distance to neighbours.

Some answers to the question of perception radius influence on the system evolution and the survival of communities are given by the plots presented in Figures 5.11, 5.12, 5.13, and 5.14 where there is one curve for each radius case as specified in the plots' legends. In these plots we show the initial 300 iterations because system converges rapidly, and later iterations provide little information. First, in Figure 5.11 we show the evolution of the number of links in the friendship graph. There is a common event for all the curves about time instant 100, that is a catastrophic drop in the number of links. In Figure 5.12 we show the evolution of population in the same period. In this case the population maintains is stable till near the 100th iteration, where the population size shows a catastrophic event similar to that of Figure 5.11, where there is a drop in agent population arount time 100. In the long run, population stabilizes forming small stable communities which are easily supported by the available resources. Notice that the diverse scale of the population and link size is due to the way we create the friendship graph which is directly related to the perception radius size. The minimal radius gives small communities, while the larger radius generates large communities which collapse around time 100. The collapse of the populations is not due to resource scarcity, because it is the simulation with the smaller radii that are more aggressive in the consumption of the resources as shown in Figure 5.13. For perception radius equal to 1 patch, the system is not far from depletion at time 50, though it recovers and the resources steadily grow, unrelated to the catastrophe at time 100. For the other radius values there is a drop in the resource availability at the initial time, followed by an epoch of growth until some time before the catastrophic event of time 100, where the resources have a small dip before going growing. Therefore we extract two main conclusions of these plots:

(1) the big communities put less pressure on the resources, and

(2) the catastrophic event is due to the mechanics of resource access and distribution not to resource availability.

The explanation of (1) and (2) is that the social pressure and the resource distribution mechanism maintain big communities locked to a small subset of resource repositories, until they are depleted. Some time after this depletion event, the community buffer of personal resource stores is also depleted leading to mass deaths in the community, until it is broken into smaller communities which move quickly to unexploited resource repositories. The evolution of mean of distances from agent to neighbours, shown in Figure 5.14, give additional information about the compactness of the families over time. It can be appreciated that after the catastrophic event there is downward trend on the distance between friends, showing that smaller and more compact failies are fovoured. Returning to Figure 5.11, notice that the larger perception radii lead to smaller surviving population. We have not included a birth operator in our system yet, so there is no way to population recovery and the system reaches an steady state where the surviving population has a life of abundant resources.

5.6 Discussion and conclusions

Homogeneous opinion spreading processes and, more specifically, resistance to this spreading in favour to opinion variety is a complex and interesting phenomenon which is far from being understood. The construction of sufficient complex agents and contexts it is yet to be done. I provide some results that show how systems that just consider attraction forces tend to result in more compact groups, whereas the system that considered attraction/reaction forces was more prone to dispersed situations. Also I have found that changes in the influence radius and in the number of neighbours considered provided different best/worst cases for each system which shows the importance of spatial behaviour when considering the spread of an opinion. However, there are some particular trends and behaviours, as it is the increasing proneness to oscilation of the systems and the growing gap between results in a very same system depending of opinion number. To extract similarities between the considered systems is higly complicatied due to the basic differences between them, however, it is noticeable how the 20 patches influence radius with two initial opinions shows a higher endurance, and the 25 nearest neighbours with three initial opinions show a drop in resistance in the first three systems, whereas the third, sixth, and seventh systems show a similar general behaviour when considering changes in influence radious as well as the fourth and fifth systems show a similar general behaviour when considering changes in nearest neighbours number for four opinions. Following this line, there is yet much more work to do, however we have provided a sound ground for future research, implementing the presented systems, and reporting some interesting, even if preliminary, group of results.

Chapter 6

Conclusions

This Chapter collects the conclusions of the three legs of this Thesis suggesting some lines for future work. Section 6.1 refers the conclusions and future work regarding the modeling of Auditory Hallucinations, Section 6.2 refers to the conclusions regarding our works on social robotics for therapeutic applications. Section 6.3 refers the conclusions on the modeling of opinion propagation in social systems.

6.1 Modeling Auditory Hallucinations

6.1.1 Conclusions

The results in this work are relevant to the study of the connectivity fingerprints of brains that are prone to experience AH, whilst the actual generative mechanism workings can not be observed because of the temporal and spatial resolution limitations of the rs-fMRI data, and the fact that most of the patients in the study did not report experiencing AH during the imaging process at the scanner. Also, results must be taken with caution because the fMRI measurements are rather indirect measurements of the actual neural activity taken place in the brain, at a much coarse scale and plagued by many kinds of noise. Regarding the AH generative mechanism hypothesis discussed in Section 3.3, the top-down causal pathway is represented in our model by the connections from AC and SbCA to IF which implement the recognition of self and the inhibition of the language recognitoin as external signal. The bottom up causal pathway is represented by the connections from ST to IF modulated by the emotional content from the amygdala in the SbCA.

6.1.2 Future work

The future direction of this reasearch line is to build a multi-agent system model that may be able to reproduce the activation behaviour of the hallucinating and non-hallucinating brains depending on the parameter settings. Eventually, it will be desirable to achieve the reproduction of the hallucination events. The basic idea is to model each anatomical area as an agent, mapping the neuronal activation, measured by surrogates such as the BOLD signal in fMRI, into an agent activation state variable. Therefore, functional connectivity between anatomical areas will be translated into inter-agent communication channels, or state influence. The model architecture is a translation of the connectivity graph in figure 3.2. The local agent state transition function can be defined as follows:

$$A_j\left(t+1\right) = \gamma A\left(t\right) + \alpha\left(\sum_i \beta_{ij} A_i\left(t\right) + S_{0j}\left(t\right)\right), \tag{6.1}$$

where $A_j\left(t\right)$ is the degree of activation of the ith area at the moment t, $\gamma < 1$ is a state declining parameter which lowers the agent activation in the absence of stimuli, α is a weight on the overall stimulation received by the agent from other agents and the external environment, it is related to the inertia of the agent, i.e. how strong it needs to be pushed to be moved, if $\alpha \ll 1$ then the agent will only respond to strong stimuli, β_{ij} is the strength of the connection between i and j areas, and $S_{0j}(t)$ the external stimulus received by the jth area at the moment t.

Agent activation can be assumed to be a continuous valued variable, but I can also set a flag variable corresponding to an observable activation when the continuous activation variable is greater than a given threshold. Such discrete activation may be of use if the overall system dynamics is governed by some kind of rules instead of the equation (6.1). On going work is experimenting with this numerical model in order to reproduce desired brain activation patterns. As a part of this work, I need to obtain from fMRI data the summarizing measures of the brain activation in order to obtain the target patterns that I aim to reproduce by our model. Specific databases, such as the one used in [135] are required to obtain such information.

Regarding the feasibility of reproducing the hallucination event, it is highly desirable to have brain imaging or activity measuring during such events in order to have the target dynamical patterns that the model is to reproduce. However, such data is very scarce and unavailable. In abstract general terms, to determine if a hallucination experience is going on, an hallucination level can be calculated. To achieve this the activation levels of attention and emotional regulation areas are added, and so are the monitoring and inhibition areas' levels. Then the last level is subtracted from the other one. Again, a threshold is yet to be set, which would specify when the brain is considered to be suffering an hallucination an when the signal is correctly inhibited. Higher hallucination level would imply a stronger hallucination, which could be understood as a lower sensation of control over it. Besides, it is also needed some kind of random start impulse, as hallucination experiences are believed to pop up from natural random impulse signals in the areas related to auditory processing which are misattributed in the ensuing processing. This random impulse, however, it would only surge in a resting state, as it would not be triggered if the area is activated. Therefore, activation level would be time dependent and with a starting random component.

This multi agent model could be of great use to improve the understanding of this phenomena, although is still a first hint of what can be done to represent the expected brain behavior of people suffering from AH. To achieve this more characteristics should be studied to build a more complex and complete model, for example resting state aberrant activation levels in certain areas, or simulation of grey matter volume alterations. In the long term, a detailed multi-agent model of auditory hallucinations would truly replicate the known behavior of said hallucinations allowing researches to deepen in an area that could improve the quality of human lifes.

6.2 Therapeutic social robotics

6.2.1 Conclusions

Interactive storytelling embdded in a natural interaction is a problem yet to be approached by the scientific community. There are interesting uses of long short term memory (LSTM) architectures regarding dialogue and speech recognition and generation [159], however they lack the intention and message transmission capability of a linear story. Most of those works are focused in the generation or continuity of the dialogue without proper understanding of dialogue semantics or concrete goal.

On the other hand, plot generation has been approached with different techniques, but have yet to be combined with the latest artificial intelligence techniques, such as generative Deep Learning. Furthermore those research works have been widely directed to video games or set in very computer dependant settings that limits the reach of the system and compromise the natural interaction.

At the same time the use of social robots have revealed itself as an interesting option to reach and connect with children, specially those with special needs. A good acceptance of this robot systems have been observed when taking the role of either peers or tutors, offering a new way for communication, and the possibility to develop new paradigms in various areas such as education, therapy, and entertainment.

In this situation I consider that these research lines can be combined for more flexible and robust systems that can provide a tool with wider applications, such as education, therapy, and/or communication support. Some of our very early work hinted in this direction with the dialogue and storytelling application embodied in a NAO that I presented in [108] with some good initial observations. However, there is a wide room for improvement that is going to be addressed in future work.

6.2.2 Future work

For the next steps of this work I believe that as Propp is able to translate any folktale into a small and quite simple formula, the oposite path could be used to generate a virtually illimited number of stories. This is important because when working in the reruting of deajusted behaviours the same model-behaviour need to be presented in different set ups, so it is considered abstractly and not a list of specific situations. Therefore it would be my main goal to automatize said folktale generation introducing a determined formula. Once we had this tool the colaboration of other therapist and social workers would be neccessary to design the interaction evolution from the very first introduction of the robot

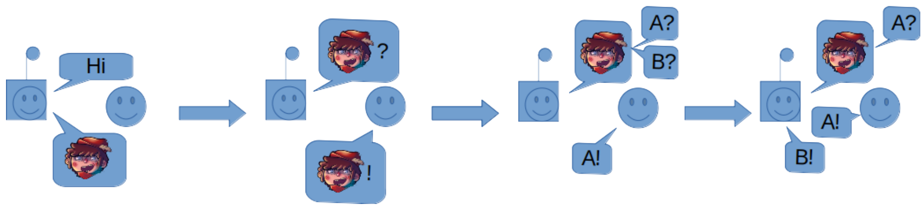


Figure 6.1: Simplified activity outline.

to the first folktales told by the robot, to the folktales built together with the child, to the interactive storytelling directed by the robot. A preliminary setup would be as the one presented in the second step in Figure 6.1 as the first is the less interactive one that I have already used in this document.

The next steps would be asking the children if they want to hear the story, as an initial way of giving the child some power over the interaction. The following would increment the interaction level by asking where the tale is going. In this part the therapist and social workers would be able to see if there is any repetitive unadaptative behaviour from the child's. Lastly the robot would present the tale and build it with the child as previous interactions, however when the detected behaviour would be shown the robot would argue with the child in order to redirect the tale to validify a more adaptative behaviour. In any phase it could be possible to go back to a previous step if the child shows any kind of disconfort.

6.3 Opinion propagation modeling

6.3.1 Conclusions

We are interested in the dynamics of opinion in human communities, which is a topic of research in many areas, such as recommender systems, security, and in general social system analysis. Resistance to homogeneous opinion spreading processes and maximization of opinion entropy in favor to opinion variety in a system with no equilibrium point is a complex and interesting phenomena with a high number of details. The construction of sufficient detailed agent-based models it is yet to be done and the phenomena itself is far from being understood. Most conventional approaches consider some kind of graph representation of the community, and model opinion spreading as some kind of epidemic diffusion over the graph. Our approach is to consider the dynamics of the agents moving in a space where they can establish new relations that affect the dynamics of opinion spreading. More precisely, we are very interested in the survival of opinions despite the pressure exerted by mainstream opinions. This phenomena is pervasive in human social societies. In this thesis we provide some results that show that smaller perception radius both when considering influence and neighborhood result in higher percentage of runs preserving opinion diversity at the end. Also, local neighborhood radius, linked both to agent movement and opinion spreading, have a significant influence in opinion variety preservation. Therefore, spatial perception can help explain the survival of minority opinions. We plan to improve the detail of the models, and to extend the computational experiments and their detailed analysis in order to improve our understanding of the mechanisms of opinion survival. Finally, we will try to fit the model to some actual social systems showing this kind of behavior using public macro-scale data.

6.3.2 Future work

Though our results are preliminary, and the model formulation is also a first approximation to the problem, we have found surprising results, which highlight the non-linear effects introduced by the consideration of the social graph based dynamics into account. The collapse of big communities despite the existence of abundant resources seems to be due to the mechanism of resource sharing working together with the need of social steem and shared opinions. Although we have not tried to model a real economical system, we think that this kind of effects appear in our socities to some extent, and may deserve consideration by experts in disciplines different from computational science. We are now trying to identify real life situations which show this kind of effect in order to define practical uses of this kind of models. For instance, it would be meaningful to establish the meaning of the perceptual radius in a fully internet connected society.

Even without a further sophistication of our model, there are a lot of questions that can be posed, such as the effect on the speed of information propagation, i.e. opinion changes, or the definition of alternative resource sharing mechanisms. The inclusion of birth operators would provide richer dynamics, leading to further questions, such as the effect of opinion inter-breeding. The way to generate the social graph can be also subject to additional modeling and experimentation. There is a pletora of model options and experiments that can be carried our from a pure especulative point of view. From a practical point of view, we look for a real life situation where we could fit the model to actual data and produce useful predictions.

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Appendix A

Multiagent systems' algorithms

A.1 System 1: Basic Gregarious System

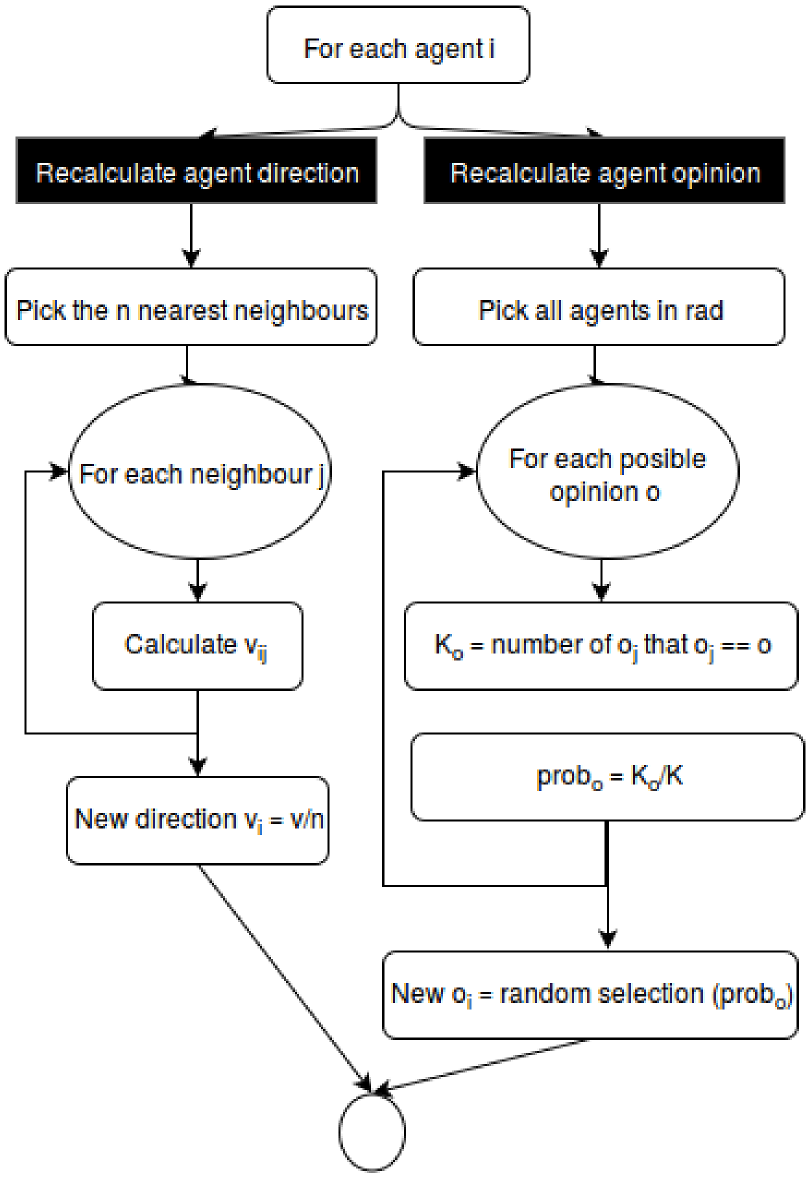

Figure A.1: The agent dynamic and opinion change model in the basic gregarious system (system 1)

A.2 System 2: Simple Peer Seeker System

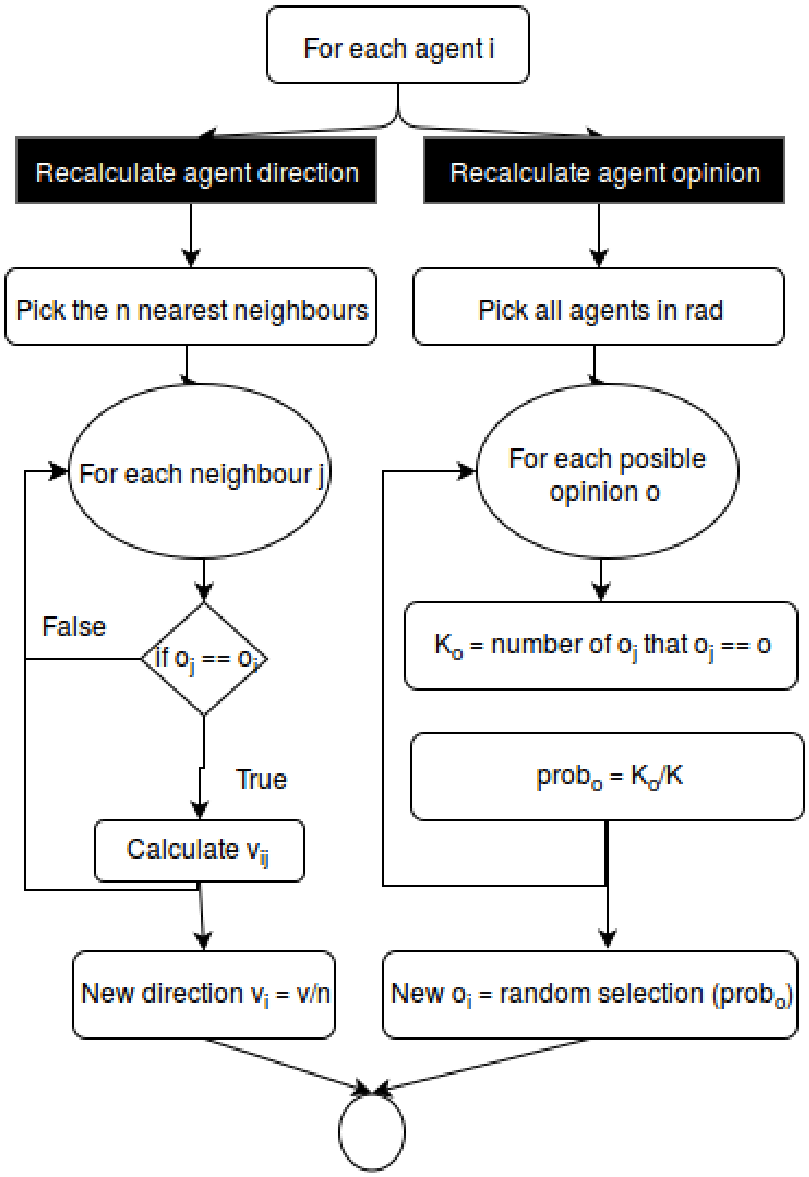

Figure A.2: An algorithm of the system 2

A.3 System 3: Ally/Enemy System

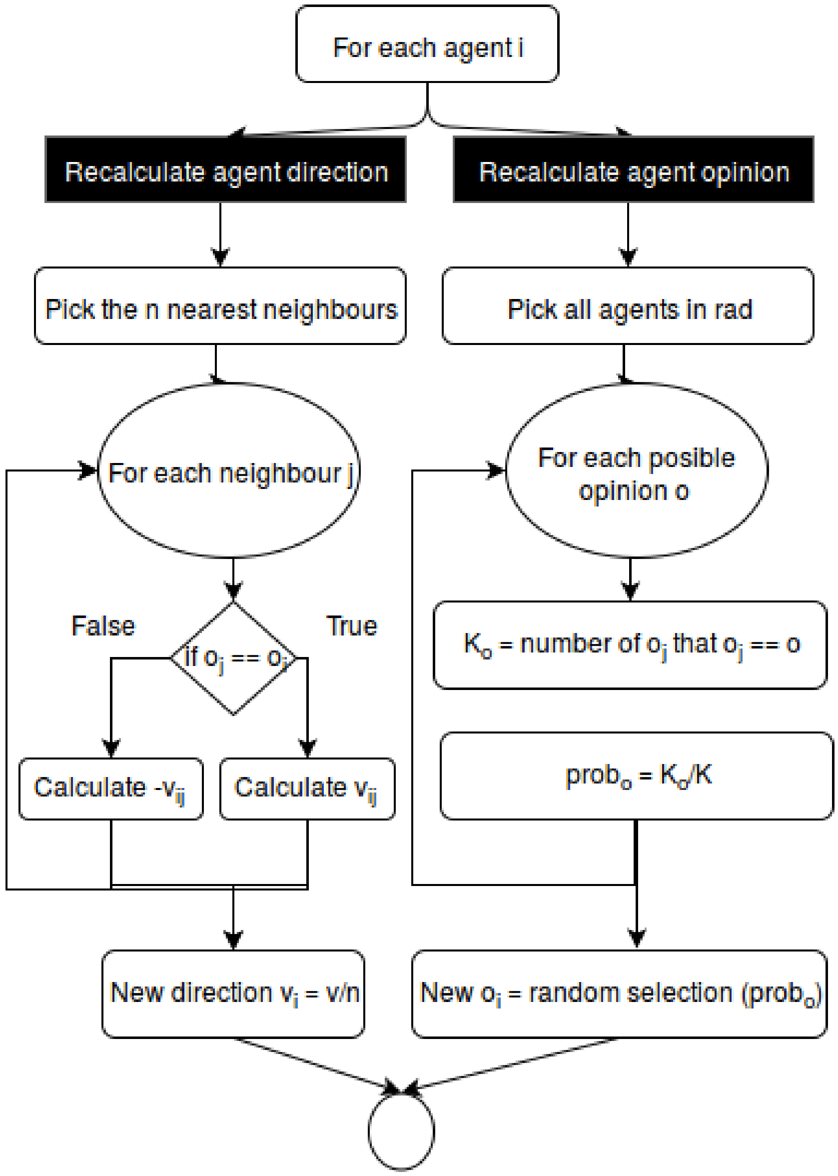

Figure A.3: An algorithm of the system 3

A.4 System 4: Ally/Enemy Randomized System

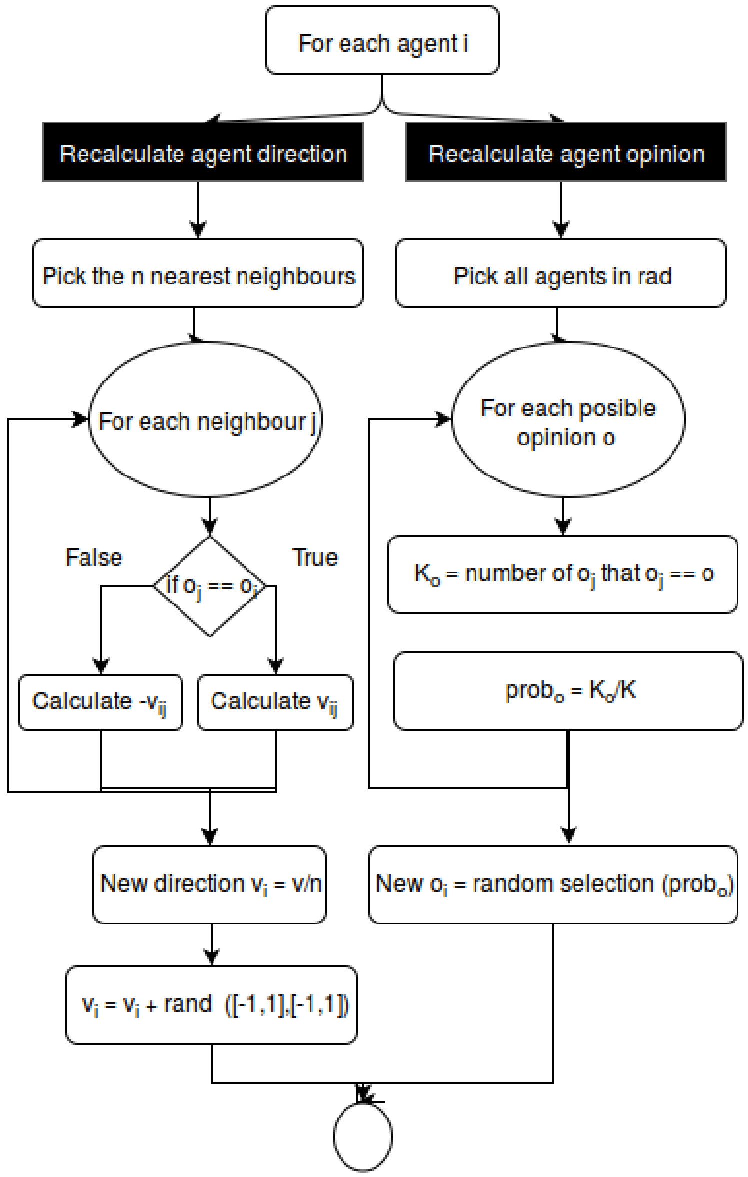

Figure A.4: An algorithm of the system 4

A.5 System 5: Ally/Enemy Randomized System with Charismatic Agents

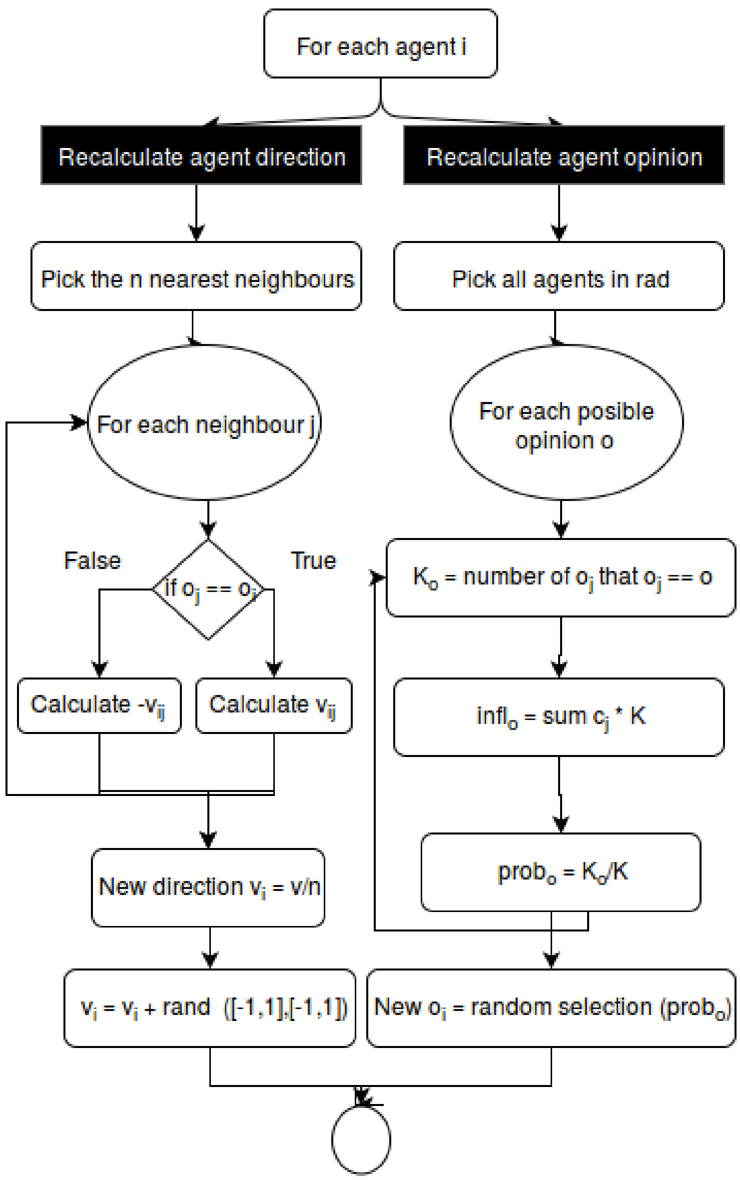

Figure A.5: An algorithm of the system 5

A.6 System 6: Ally/Enemy Randomized System with Charismatic/Stubborn Agents

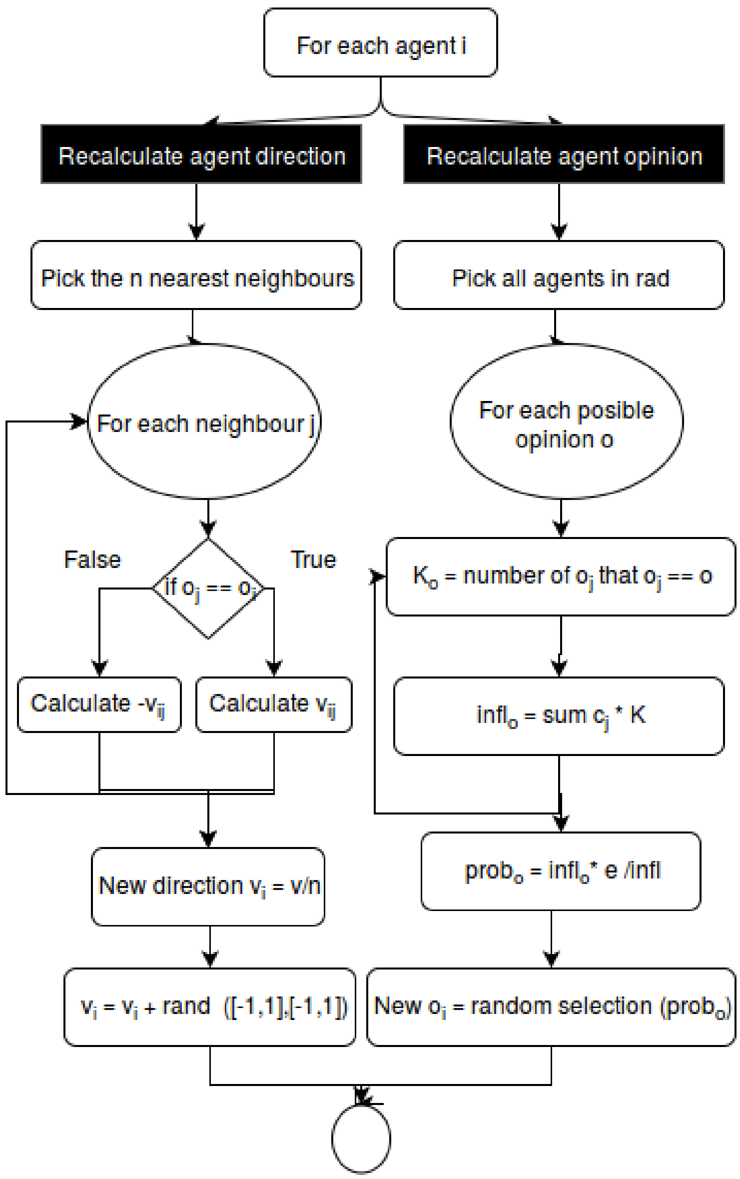

Figure A.6: An algorithm of the system 6

A.7 System 7: Ally/Enemy Randomized System with Conservative Agents

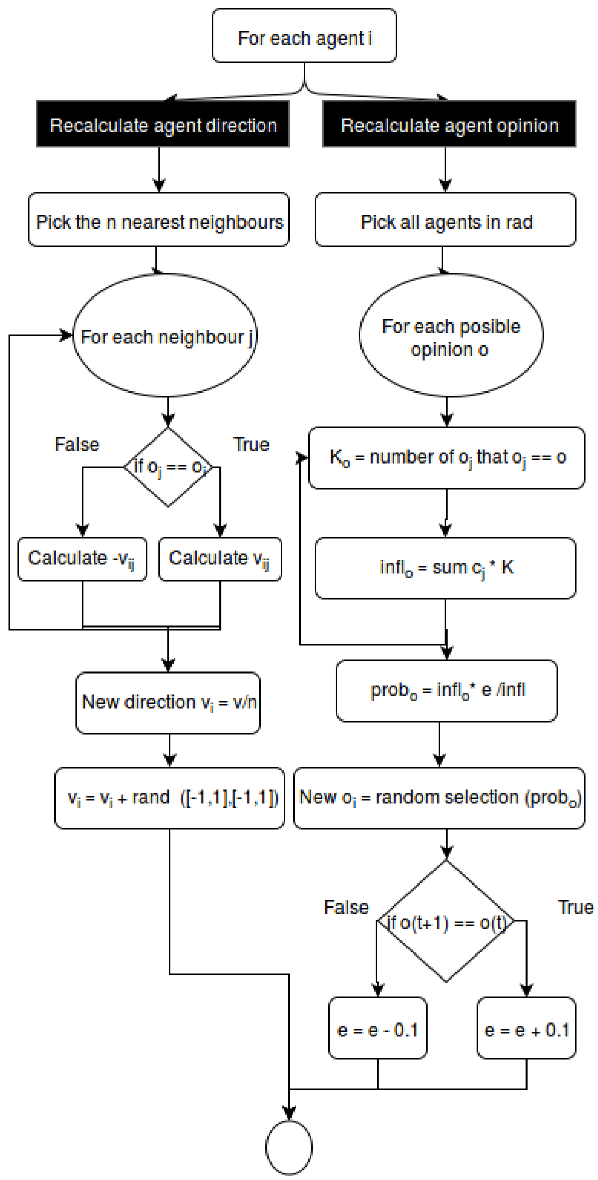

Figure A.7: An algorithm of the system 7

A.8 System 8: Ally/Enemy Randomized System with Varied Attitude Agents

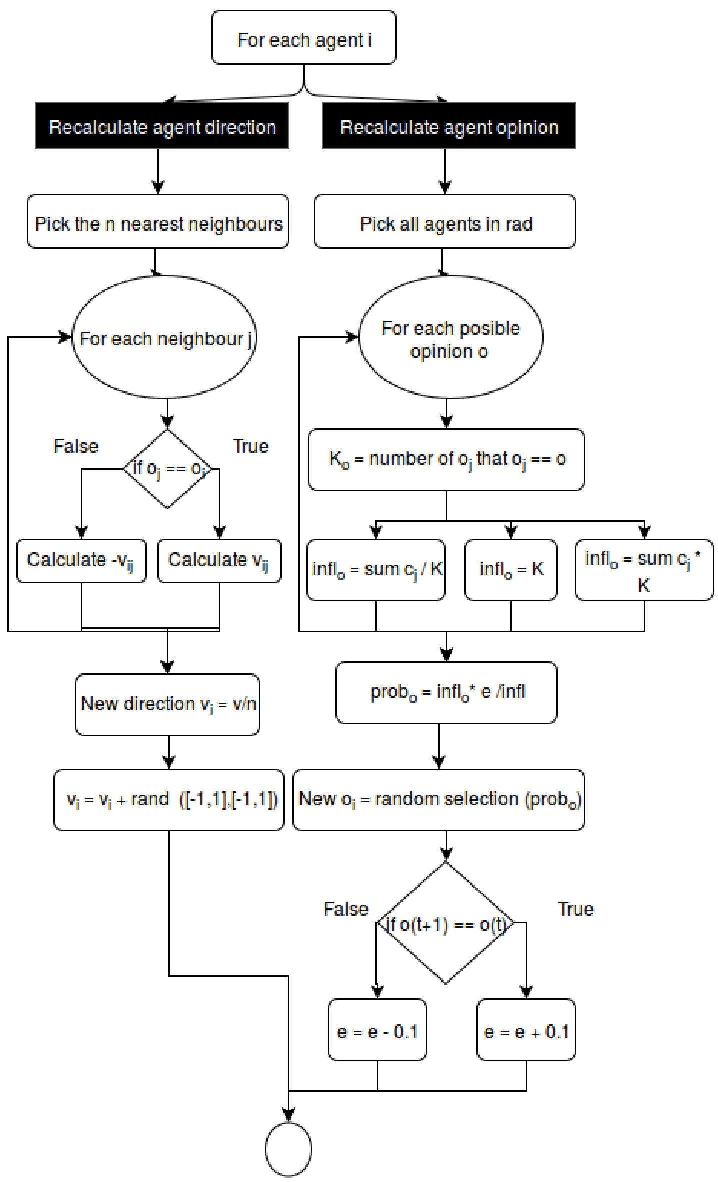

Figure A.8: An algorithm of the system 8

A.9 System 9: Ally/Enemy Randomized System in Social Networks

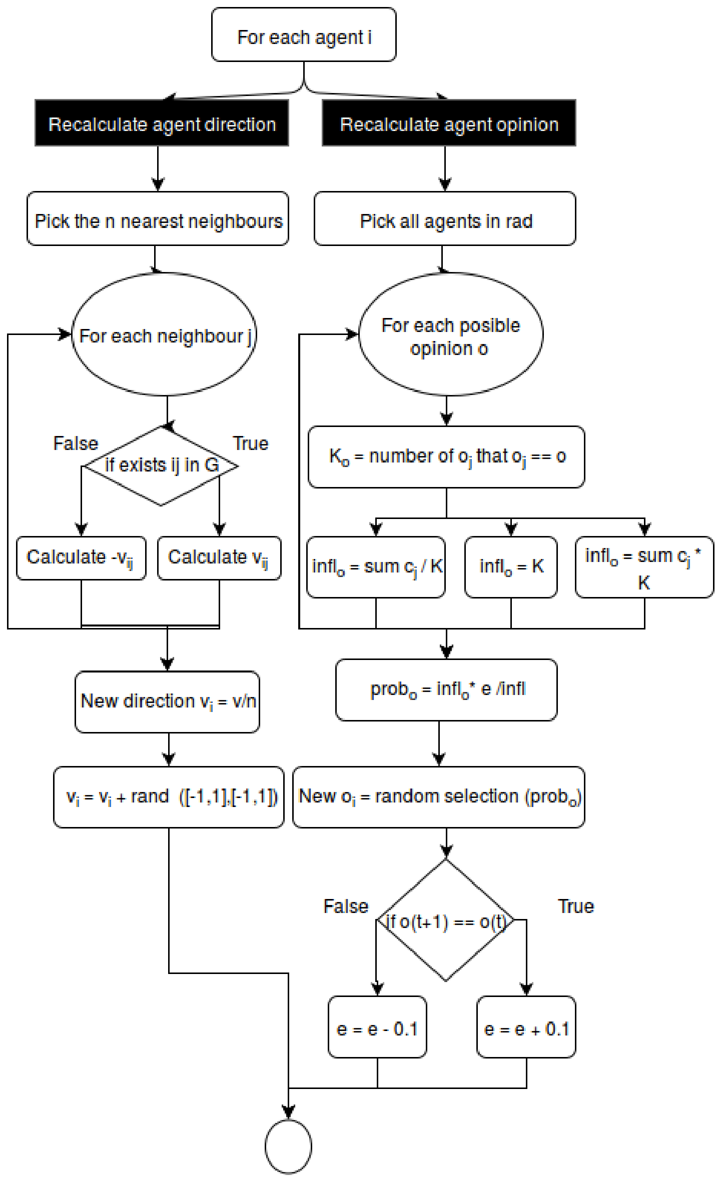

Figure A.9: An algorithm of the system 9