ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL OF SCIENCE ENGINEERING AND TECHNOLOGY

A BRAIN-INSPIRED COGNITIVE ARCHITECTURE FOR DEVELOPMENTAL AND SOCIAL HUMAN-ROBOT INTERACTION

Ph.D. THESIS

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JANUARY 2019

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To my lovely wife Sare Funda Dağlarlı,
and our handsome son Evren Önder Dağlarlı,

FOREWORD

This thesis aims to combine the recent developments in cybernetics, cognitive science and neuroscience with the viewpoint of control engineering, computer science and to guide the autonomous systems and robotics researchers about intelligent robot control architectures. As a student of control engineering Ph.D. program at ITU, I would like to thank to all the instructors and coordinators of the program for giving an opportunity, their courage and enthusiasm.

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ABBREVIATIONS

ADHD	**:** Attention Deficit Hyperactivity Disorder
AI	**:** Artificial Intelligence
ANN	**:** Artificial Neural Network
App	**:** Appendix
BICA	**:** Brain-Inspired Cognitive Architecture
BP	**:** Backpropagation
CNN	**:** Convolutional Neural Network
DAC	**:** Distributed Adaptive Control
DFT	**:** Dynamic Field Theory
DNF	**:** Dynamic Neural Field
EB	**:** Elementary Behaviour
EEG	**:** Electroencephalography
fMRI	**:** Functional Magnetic Resonance Imaging
HRI	**:** Human-RobotInteraction
ITU	**:** Istanbul Technical University
LTM	**:** Learning Long Term Memory
ML	**:** Machine Learning
PR	**:** Pattern Recognition
RL	**:** Reinforcement Learning
SOM	**:** Self Organizing Map
STM	**:** Short Term Memory
SVM	**:** Support Vector Machine
WM	**:** Working Memory
WTA	**:** Winner Take All

SYMBOLS

$\mathbf{V_j}$	: Potential of j th neuron (mV)
$\mathbf{C}$	: Capacitance
$\mathbf{E_i}$	: Reversal potential related to ion channels
$\mathbf{g_i}$	: Conductance
θ_i	: Gate variable
$\mathbf{I_{Ext}}$, $\mathbf{I_L}$	: External input and leak current
$\mathbf{I_{Ca}}$, $\mathbf{I_{Na}}$, $\mathbf{I_K}$	: Calsium, Sodium, Potasium ion channel currents
$\mathbf{u}$	: Recovery variable
$\mathbf{W_{ij}}$	: Weight matrix
$\mathbf{r_k}$	: Spiking rate
τ	: Time constant
$\mathbf{t}$	: Time
$\mathbf{f_{rate}}$	: Spiking rate threshold
$\mathbf{h^{e,i}}$	: Impulse response function
$\mathbf{H^{e,i}}$	: Amplitude of impulse response
$\mathbf{U(x,t)}$	: Activation of neural field
$\mathbf{S(x,y)}$	: Exegenous input connection matrix
$\mathbf{I(y,t)}$	: Exegenous input field activation
$\mathbf{h}$	: Bias of neural field activation
$\mathbf{w_{exc}}$	: Excitation coefficient of neural field
$\mathbf{w_{inh}}$	: Inhibitation coefficient of neural field
$\mathbf{s_j}$	: Exegenous input connection coefficient
ℓ	: Neural field activation spatial distance
σ_{exc}	: Excitation variance of the neual field activation
σ_{inh}	: Inhibitation variance of the neual field activation
α	: Learning rate
$\mathbf{E}$	: Learning error
$\mathbf{i^{c,s}}$, $\mathbf{i^r}$	: Color, shape and robot’s selection index of the objects
$\mathbf{r_q}$	: Robot’s hand points
$\mathbf{x_o}$, $\mathbf{x_o^r}$, $\mathbf{x_o^h}$, $\mathbf{x_h^r}$	: Object locations and the locations pointed by robot and human
$\mathbf{y_{sp}^r}$, $\mathbf{y_{TE}^{c,s}}$	: Speech output (words) and recognized objects (color or shape)
$\mathbf{TF_t}$	: Temporal memory fragment
$\mathbf{p_{c,s}^t}$	: Temporal perception performance score related to color and shape
$\mathbf{A}$, $\mathbf{V}$	: Arousal and valence values
$\mathbf{rew_{am}}$, $\mathbf{rew_{bg}}$	: Rewards of amygdala and basal-ganglia
$\mathbf{ad}$, $\mathbf{dp}$	: Parameters related to adrenalin and dopamine
$\mathbf{s_{bg}}$, $\mathbf{s_{1,2,3,4}}$	: Basal-ganglia states
$\mathbf{a_{bg}}$	: Basal-ganglia action
$\mathbf{epi_{resp}}$	: Episodic memory response

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A BRAIN-INSPIRED COGNITIVE ARCHITECTURE FOR DEVELOPMENTAL AND SOCIAL HUMAN-ROBOT INTERACTION

SUMMARY

In this study, a novel cognitive architecture is proposed to realize computational model of limbic system and cognitive perceptual system inspired by human brain activity, which improves the interaction between human and robot, based on joint attention during the experiments. Using human-robot interaction (HRI), this brain-inspired framework can become a suitable solution for problems related to establishing and maintaining the joint attention.

After the presentation of the problem, literature survey, statement of hypotheses and research questions in chapter 1, some background material about the methods used throughout the thesis is described in chapter 2. Some candidate methods including spiking neural networks, neural mass and dynamic neural fields are investigated. The neural mass model deals with dynamics of neuron population. Population dynamics reflects responses as mean firing rates of population including spiking neurons. The dynamic neural field deals with field dynamics. In field dynamics, the neural activity behaves like wave packets which travel along the neural field. Computational mechanisms are mainly placed on bio-physical plausible neural structures with different dynamics. Also, different learning and adaptation algorithms are applied to the regions of computational models in the background of proposed cognitive perception system.

In chapter 3, the computational framework realizes perceptual cognition skills via thalamus and sensory cortices with multi-modal stimuli so that it provides to help achieving of recognition and modelling perceptual attention tasks for a humanoid robot which can easily communicate with its environment. In chapter 4, computational models of the proposed limbic system including the amygdala, hippocampus, and basal ganglia modules realize some cognitive processes such as emotional responses, episodic memory formation, and selection of appropriate behavioural responses, respectively. Using this system in the humanoid robot, success rates and response times of preschool children are evaluated so that attention deficiencies of them can be diagnosed and improved during the proposed interaction gameplay.

Experimental evaluation and verification tests have been performed to observe and control the physical and cognitive processes of the robot in a developed software framework embodied humanoid robot platform. Several interaction scenarios are implemented to monitor and evaluate the performance of computational model in the system architecture. Finally, results of the methodology used in this study are comprehensively compared with the different models for discussion of relative superiority with respect to each other. According to the findings, the proposed computational brain inspired cognitive architecture is effective in the successful establishment of the joint attention task between the humanoid robot and the human.

GELİŞİMSEL VE SOSYAL İNSAN-ROBOT ETKİLEŞİMİ İÇİN BEYİN ESİNLİ BİLİŞSEL MİMARİ

ÖZET

Bu çalışmada, insan beyin aktivitelerinden ilham alarak, insan ve robot arasında müşterek dikkat tabanlı etkileşimi geliştiren limbik sistem ve bilişsel algı sistem hesapsal mimarilerinin gerçekleştirilmesi amaçlanmıştır. Bu iki sistem çalışmanın temelini oluşturan hesapsal genel yapının alt mimarileridir. Frontal, temporal, parietal, görsel korteks (occipital), beyin kökü, beyincik ve omurilik gibi genel yapılardan oluşan insan beyni oldukça karmaşık bir biyolojik bilgisayar olduğundan tezin kapsamı sadece limbik sistem, görsel korteks, temporal ve parietal loblarla sınırlandırılmıştır. Ayrıca insan robot etkileşiminin kullanılmasıyla, bu beyin esinli mimari müşterek dikkatin kurulması ve sürdürülmesi ile ilgili problemler için uygun bir çözüm olabilir. İnsan robot etkileşimi araştırmalarında insan hareket ve davranışlarına en çok benzerliği bulunan insansı bir robot tercih edilmiştir. Giriş kısmında çalışmanın amaçlarının vurgulanmasının ardından tezin kapsamındaki geçmiş çalışmalara ilişkin geniş literatür taraması yapılmıştır. Ek olarak çalışma ile ilgili zorluklar ve problemler analiz edilmiştir. Tezin performansının değerlendirilmesi için araştırma soruları ve hipotezler belirlenmiştir. Tezin literature yaptığı katkılar ve getirdiği yenilikler detaylı olarak ele alınmıştır. İlk kısmın sonunda tezin organizasyon planı verilmiştir.

İkinci bölümde, tezde kullanılançeşitli yöntemlere yönelik bazı ön bilgiler verilmiştir. Tezde önerilen işlemsel limbik sistem mimarisinin alt yapısını oluşturan hesapsal model doğrusal olmayan, dinamik çok kipli davranışlar sergiler. Dürtüsel sinir ağları, sinirsel kütle ve dinamik sinirsel alanları içeren bir takım aday metodlar bu bağlamda incelenmiştir. Bunlara ilişkin simulasyon çıktıları sunulmuştur. Sinirsel kütle sinir hücre populasyon davranışını ele alır. Populasyon dinamiği dürtüsel sinir hücreleri barındıran sinir hücresi populasyonunun ortalama ateşlenme oranı olarak tepkileri yansıtır. Dinamik sinirsel alan dürtüsel sinir hücrelerinin dinamik alan davranışını ele alır. Alan dinamiğinde, bir sinirsel aktivite sinirsel alan boyunca dolaşan dalga parçaları gibi davranır. Hesapsal mekanizmalar değişik dinamikleri içerisinde barındıran biyo-fiziksel sinir yapıları model alır. Ek olarak insan beyni ile ilgili anatomik yapılar tanıtılmıştır. Sonrasında makina öğrenmesi prensipleri ile ilgili temel bilgi verilmiştir. Tezin uygulama ve deneylerinde kullanılması amacıyla deneysel platform olarak düşünülen insansı robot yazılımsal ve donanımsal özellikleri bakımından detaylı olarak tanıtılmıştır.

Üçüncü bölümde insan beynindeki talamus, görsel korteks, parietal ve temporal lob kısımlarını kapsayan bilişsel algı sistemi modellenmiştir. Bu sistemin kapsamındaki bilişsel fonksiyonlar bir insansı robot için gerçeklenmiştir. Bu bölümde insanla robot arası etkileşim sırasında insanın bilişsel algı mekanizmasından yola çıkılarak, ortak dikkatin modellenmesi ve tespit edilmesi amaçlamaktadır. Talamus robotun

sensörlerinden gelen (eklem enkoderlerinden gelen bilgi, mikrofondan gelen ses sinyali ve kameradan gelen görsel veri) bilgilerin ilk olarak işleme tabi tutulduğu mekanizmadır. Bu kısımda çeşitli ön işlemler icra edilir. Daha sonra görsel kortekste görüntü çeşitli filtrelerden geçirilir. Ek olarak blob analizi ile nesneler tespit edilerek, nesnelere ilişkin ilgi bölgeleri saptanır. Bu noktada temporal lob modülüne veri transferi için nesnelere ilişkin renk ve şekilleriyle alakalı öz nitelik çıkartım süreçleri yürütülerek özellik vektörleri bulunur. Diğer taraftan parietal loba veri transferi için nesnelerin uzaysal konumları bulunur. Temporal algı modülünde, talamusta hesaplanan ses öznitelik vektörü yardımıyla saklı Markov modeli kullanılarak ses tanıma görevi icra edilir. Bu modülde nesnelere ilişkin renk ve şekil tanıma için k-en yakın komşuluk, destek vektör makinası, naïve Bayes, karar ağacı, yapay sinir ağı (çok katmanlı algılayıcı) kullanılmıştır. Ek olarak derin öğrenme metodu olarak evrişimsel sinir ağı uygulanmıştır. Uzaysal algı mekanizması olarak parietal modülde görsel olarak yeri tespit edilen nesnelerin robot kolu tarafından gösterilmesini öğrenmek amacıyla regresyon modelleri kullanılır. Sonuçları karşılaştırmak amacı ile destek vektör makinası, karar ağacı, doğrusal olmayan regresyon ve çok katmanlı algılayıcı modelleri kullanılmıştır. Sonrasında temporal ve parietal (uzaysal algı) merkezlerinden gelen verilerle ortak dikkatin belirlenmesi sağlanmıştır. Elde edilen bulgular robotun bilişsel algı mekanizmasının uzaysal ve uzaysal olmayan (temporal) algı başarımlarının oldukça yüksek olduğunu göstermektedir. Örneğin uzaysal algı mekanizması için düşünülen regresyon modelleri %93 ortalama başarı yakalamıştır. Temporal (uzaysal olmayan) algı mekanizmalarında renk ve şekil tanıma için kullanılan sınıflandırma modelleri renk tanıma için ortalama %94, şekil tanıma için ortalama % 95 başarım değerleri sağlamıştır. Ek olarak ses tanımadaki hata oranı %12 ve insansı robotun eliyle nesneyi işaret ederek göstermesindeki hata payı %14 olmuştur.

Dördüncü bölümde, çevresiyle kolaylıkla iletişim kurabilecek bir insansı robot için duygu, anısal bellek ve dikkatin modellenmesi gibi bilişsel görevlerin gerçekleştirilmesi amacıyla hesapsal limbik sistem mimarisi geliştirilmiştir. Olayların (yapılan hareket ve mimikler) başarım oranı prefrontal korteksin basitleştirilmiş bir hesapsal modeli içinde oluşan çalışma belleği tarafından değerlendirilir. Bu önerilen yapıda, limbik sistemin kısımları olan amidala, hipokampus ve basal-ganglia modüllerini içeren hesapsal modeller gerçeklenmeye çalışılır. Amidala modülü algısal modülden iletilen öznitelik verisine dayanarak duygusal ifadeleri tespit eder. Aynı şekilde algısal modülden iletilen öznitelik verisi yardımıyla hipokampus modülü insan-robot arasındaki etkileşimsel olayları anısal bellek oluşumu ile kayıt altına alır. Duygusal aktiviteler ve anısal bellekten gelen veriler uygun davranışsal tepkilerin seçimi gibi bilişsel süreçler için basal-ganglia modülüne aktarılır. Basal-ganglia çıkışından aktarılan veriler insansı robotun servo motorlarına iletilir. Robot insandan gelen tepkileri gözlemler. Bu tepkilerin hızı ve doğruluğu robotun insan davranışlarını analiz etmesinde etkilidir. Bu kısımdaki deneylerde elde edilen sonuçlara göre dinamik sinirsel alanların, sinirsel kütle modeline göre daha iyi sonuç verdiği görülmüştür. Ek olarak insansı robotla yapılan deneylerde, öğretmenle yapılan deneylerle karşılaştırıldığında normal çocukların oluşturduğu grup ve dikkat eksikliği çeken çocukların olduğu grup arasındaki farkın azaldığı gözlemlenmiştir.

Değişik öğrenme ve uyarlama algoritmaları bu önerilen mimari içindeki hesapsal modellere uygulanır. Bir insansı robotun fiziksel ve bilişsel süreçlerinin gözlemlenebildiği ve kontrol edilebildiği deneysel değerlendirme ve doğrulama testleri bu insansı robot platformu içinde bulunan gelişmiş sistem mimarisi tarafından yürütülür. Sistem mimarisinin çalışabilmesi için yazılım geliştirme ortamına ek olarak bazı temel kütüphanelere ihtiyaç vardır. İnsansı robotun kendi yazılım geliştirme paketi, ses ve görüntü verilerinin alınabilmesi için ek yazılımsal destek paketleri ve kütüphaneleri buna örnek olarak verilebilir.

Hesapsal modeli barındıran sistem mimarisinin performansını değerlendirmek ve izlemek için insanla robot arasında uygulama olarak çeşitli etkileşim senaryoları icra edilmiştir. Sonuçların değerlendirmesinde istatistiksel analizlerle sistem başarımı irdelenmiştir. Ek olarak, bu tez çalışması içinde kullanılan metodolojilerin sonuçları birbirlerine karşı ilişkisel üstünlüklerini tartışmak için değişik modellerle ayrıntılı olarak karşılaştırılmıştır. Ayrıca insanla ilgili deneyler, konusunda uzman psikolog denetiminde gerçekleştirilmiştir.

1. INTRODUCTION

People having disabilities, infants, elders and patients need better communication abilities to interact with their environment. There are many accessory robotic equipment, which have developed in recent years so that life standards of these people are increased. Due to their bipedal structure and physical capabilities, humanoid robots are very compatible to interact with human nature [1].

Like personal assistants, humanoid robots are interacting with humans in different ways. Today, autonomous humanoid robots are widely used in entertainment, education, research, home services, nursing jobs rather than jobs in industrial facilities to perform deterministic, repetitive tasks. In daily life, humanoid robots can help in these social areas while they are undertaking assistive support and rehabilitation tasks for nursing or care working services [2].

Humanoid robots enhanced with embodied cognitive abilities can be used to assist disabled individuals struggling to interact with their social environment by guiding their accessibility and communication [3]. It is also anticipated that they will take on more duties in future. Recent advancements in paradigms of artificial intelligence and cognitive neuroscience can contribute to evolution of their technologies[4]. Currently, humanoid robots are able to response to perceptual stimuli, simultaneously perform complex decision-making and recursive task processing transactions (e.g., autonomously planning behaviour selection and execution). In the following decades, it is expected that modern artificial intelligence (AI) architectures developed for autonomous humanoid robots will be based on brain-inspired transactions, which will constitute the principles of cognitive science and neuroscience in the future. As a software framework of the future, the computational approximation of human brain should exhibit features of higher cognitive abilities such as deliberative planning, meta-reasoning, re-organizing, linguistic capabilities, consciousness and self-awareness.

Humanoid robots used in social areas need some human like extraordinary cognitive skills such as reasoning, decision making, problem solving. In order to realize them, these embodied skills should organize very complex behaviour patterns rather than performing more deterministic or repetitive tasks [5]. It is a quite challenging issue that high level cognitive skills including imitation of emotional responses, attention modulation, learning plasticity, modelling of environmental awareness (e.g. robot's world model or model of human(s) interacting with robot), organizing associative memory models should be achieved. Under uncertain states and conflicting requests, when the software framework of a computational cognitive model for humanoid robots able to cope with multi-objective and goal-directed action-selection problems is developed, deficiencies in coordination between multi-modal perceptual stimuli increase these problems.

In the future, humanoid robots competing with human intelligence may socially interact and collaborate in every social area behaving like a part of the humanity so that they increase life standards of the society.

1.1 Purpose of Thesis

In the nature, cognitive and mental skills could be biologically realized via some cortical and cerebral lobes in the human brain [6]. Some cortical and cerebral lobes or zones are responsible from cognitive functions. Therefore, to achieve these goals, it is essential to investigate the biological nature of cognitive systems and to develop computational equivalents of them from artificial intelligence infrastructure viewpoint of a humanoid robot. In order to realize that, the main purpose of this study intends to construct a suitable large-scale computational AI framework of cognitive model for a humanoid robot imitating human psychology (e.g. consciousness, awareness, attention, behaviours, emotional expressions) and intelligence (e.g. reasoning, perception, problem solving, communication, inference, planning, learning), to exhibit similar functions of the human brain [6].

Beyond the classical AI paradigms and approaches, this idea covers functional modelling of some cerebral regions (e.g. cerebellum, midbrain, limbic system, prefrontal cortex, motor cortex, visual cortex, temporal and parietal lobes) inspired from anatomical structure of the human brain. The characteristics of computational infrastructure which includes different mathematical models and algorithms could exhibit some properties of stochastic and nonlinear dynamics (e.g., chaotic behaviours, multi-modal or strange attractors, chattering) [6].

To achieve goals of the thesis, concepts and scopes related to the thesis include theoretical modelling, simulating and testing of the developed system architecture for the humanoid robot. Due to high-level computational costs, in addition to a humanoid robot platform, a high performance computer system as a host is employed for implementation rather than directly embedding the cognitive architecture into a humanoid robot platform.

1.2 Literature Review

In recent years, works about computational cognitive architectures developed for human-robot interaction with humanoid robots have rapidly increased and they will be expected to rise as one of the emergent issues in the future [4]. Up to now, there are several instances, which can count as significant qualification. Chronologically, they can be investigated by dividing into several sub-generations which include biologically inspired cognitive architectures, behaviour based and artificial emotion driven AI frameworks [5]. As a reverse engineering perspective of AI, the state of the art paradigms like nature inspired methodologies which have been developed in the last 20-30 years can shed light to developing a future artificial mind of humanoid robots to achieve better multi modal and dynamic human-robot interaction for developmental social robotics. In addition, combinations of these studies are discussed for developing alternative hybrid solutions into structure of large-scale central nervous system.

Recently, computational cognitive architectures have been developed for human-robot interaction (HRI) with humanoid robots to solve behaviour-planning problems. Such projects are rapidly increasing, and they are expected to continue to expand as an emergent technology in the future.

Some very good examples of computational architecture based on dynamic neural fields (DNF) were presented in the works [7] and [8]. In [7], Y. Sandamirskaya establishes the relationship between DFT and soft winner take all (WTA) networks to integrate DFT mechanisms shown in figure 1.1. It is possible to realize some properties such as the stabilization of working memory, the coupling of sensory systems onto motor dynamics, intentionality, and autonomous learning through these computational structures.

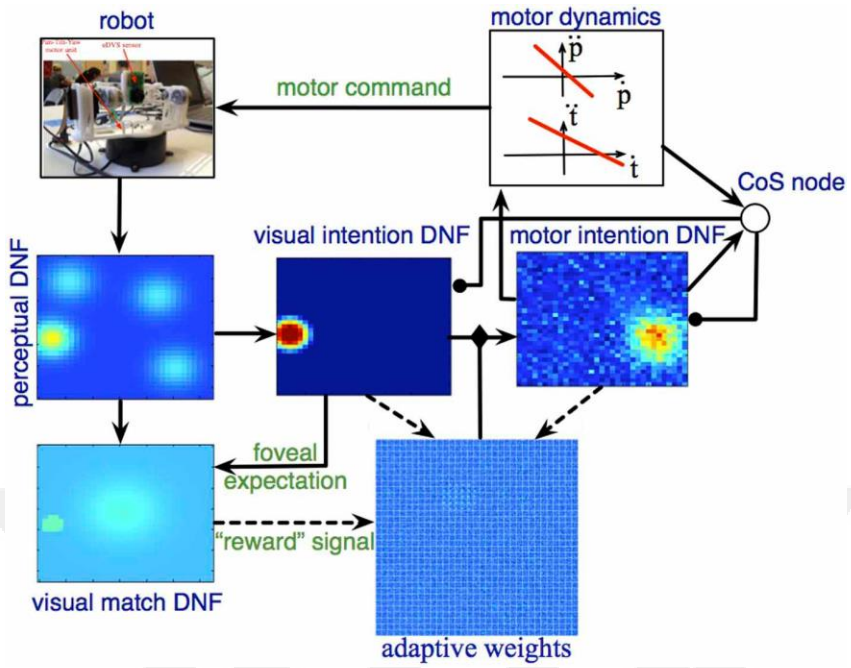


Figure 1.1 : Dynamic neural field architecture for sensory-motor mapping [7].

Richter et al. [8] proposed an autonomous neural dynamics framework in 2014. Representation and transformation of spatial perception are provided by neural activation fields. An architecture of dynamic nodes establish interaction to transfer information between perceptual fields. Cognitive skills like attentional selection of individual objects in a scene, location mapping of an object-centred reference frame, and evaluation of matches to relative spatial terms are realized with these computational mechanisms[8]. The nodes organize discrete time processing steps sequentially. These steps arise from instabilities in continuous time neural dynamics. In these studies, DNFs are introduced as a suitable domain for modelling embodied cognition.

Duran et al. conducted a promising study on DNF utilizing a reinforcement learning method for HRI in 2011 [9]. In this work, tasks of a humanoid robot are modelled as submodules (elementary behaviour (EB) model) and the reinforcement learning procedure teaches a policy of behavioural switching between them. Using the NAO humanoid robot platform, they propose a mathematical formulation to incorporate these modules. This study (Figure 1.2) is a good instance of the successful execution and learning of dynamic sequences. Through comparison of two reinforcement learning methods applied to sequence generation, results are presented for both simulation and implementation.

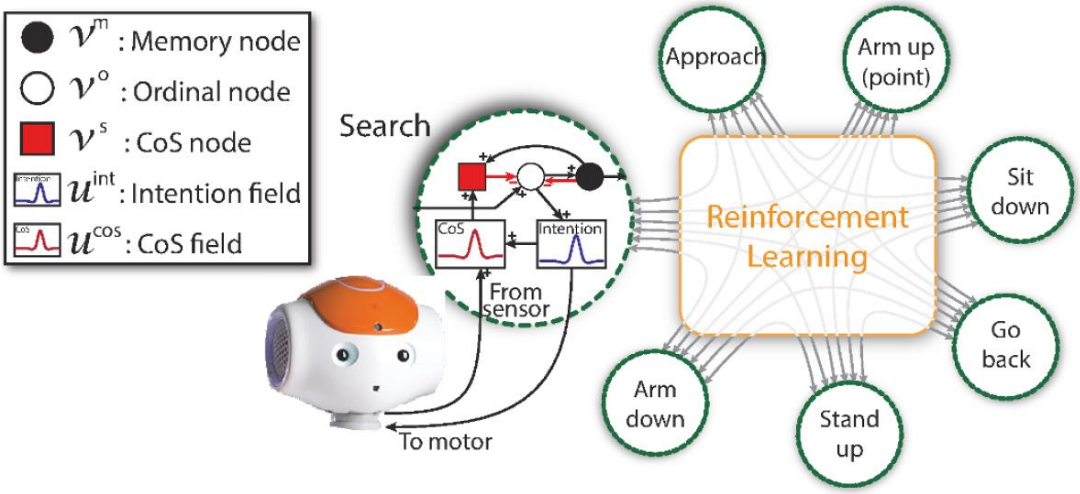


Figure 1.2 : Dynamic neural field utilizing a reinforcement learning [9].

Furthermore, an emotional biologically inspired cognitive architecture (eBICA) based on mental schemas was published in 2013 [10]. This study (Figure 1.3), describes a complete architecture for representation and processing of emotional expressions in a cognitive framework, called ‘‘emotional biologically inspired cognitive architecture’’ (eBICA) since human-like artificial emotional intelligence is important for adaptation of future robots with the human society. Emotional responses were simulated synthetically to all cognitive representations and processes by modifying the main building blocks of the prototype architectures [10]. Additionally, emotional modulation for behaviour processing performs clustering of the emotional states in the arousal-valence domain. Control patterns of appraisals and semantic spaces giving values to appraisals can represent social emotions, that the major components are appraisals related to attributes with schemas and mental states, moral schemas. In Samsonovich’s study, the major components are schemas and mental states, with moral schemas embodied into appraisals as attributes[10]. The patterns of social emotions and semantic spaces are represented and controlled by these appraisals. In an experiment involving human subjects and virtual agents, results of proposed principles are tested based on a simple paradigm in a virtual world. It is shown that eBICA with moral schema can easily manipulate human behaviour through the selected approach. The framework could be useful for collaboration of virtual partners with humans, self-regulated learning of virtual agents, and realization of reasonable emotional intelligence.

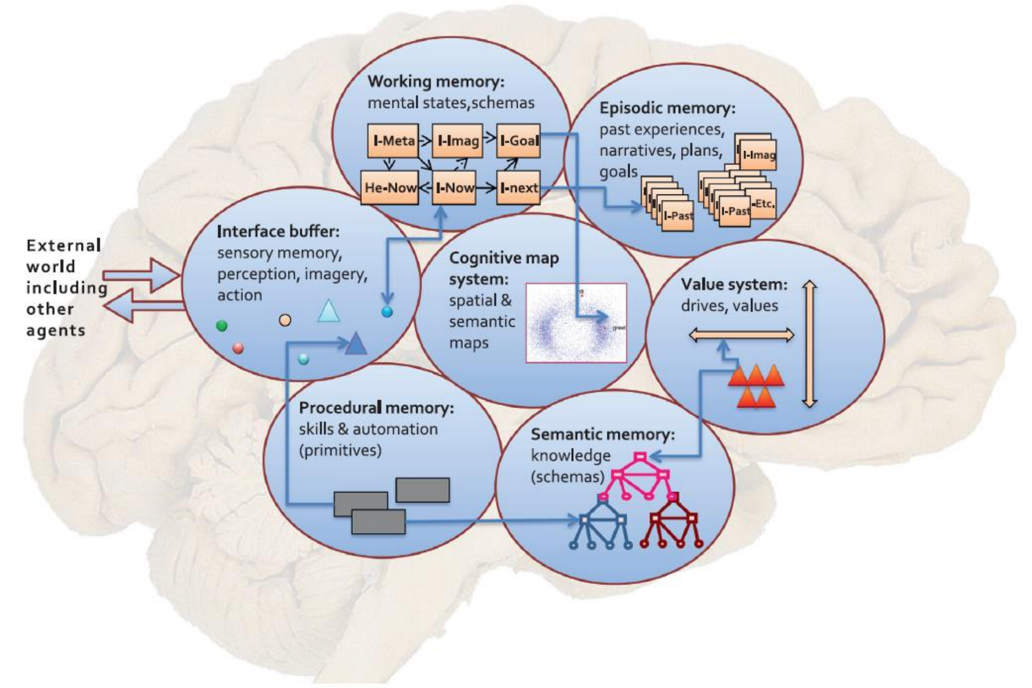


Figure 1.3 : Emotional Biologically inspired Cognitive Architecture [10].

Proposed principles are tested in a simulation with human subjects and virtual agents, based on a basic approach in artificial environment [10]. The eBICA can account for human behaviour in the chosen approach with moral schemas. The model shows clustering of social emotions and allows the emotions via novel mathematical description. A unique architecture is proposed for implementation of believable emotional intelligence in artefacts, necessary for emotionally informed behaviour, collaboration of virtual partners with humans, and self-regulated learning of artificial agents [10].

A recent study on design principles underlying the mind, brain, and body nexus (MBBN) published in 2012, authored by Paul F.M.J. Verschure[11] was a brain inspired cognitive architecture composed of several computational blocks.

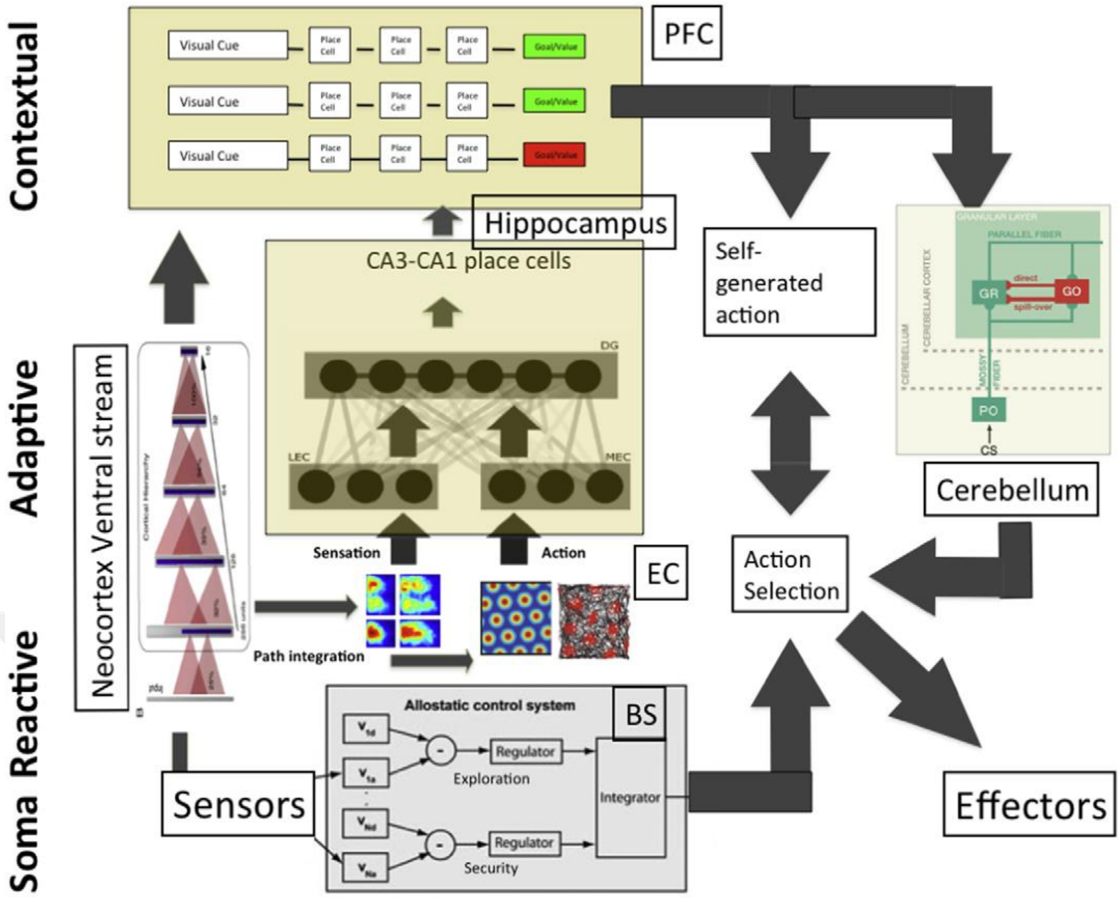


Figure 1.4 : NeuroDAC Architecture [11].

The fact that the brain maintains stability between an embodied agent and its environment through action is ensured via neural modelling of the Distributed Adaptive Control (DAC) [11]. DAC (Figure 1.4) presumes that the brain should answer four fundamental questions called as H4W problem (e.g., why, what, where, when) while the brain is sustaining stability between an embodied agent and its environment through action. The DAC theory is proposed as a robot based neural architecture composed of two complementary structures including layers and columns[11]. The DAC theory organized in two complementary structures (layers and columns) is described as a computational neuro-cognitive architecture for a robot. The reactive, adaptive and contextual layers define developmental stages of the architecture[11]. The columnar structures, including the processing of states of the world, the self, and the generation of action, describe functional parts of the architecture. In examples of application scenarios, hypotheses related to the work are validated using humanoid and mobile robots, neurorehabilitation and the large-scale interactive space combines the general perspective of DAC's explanation of MBBN.

In 2012, Sengor et al. presented a robot model based on cortico-striato-thalamic circuits, by developing a computational model of the basal ganglia for a mobile robot [12]. The main purpose of this work is to show the potential use of robot models for implementing intelligent systems to inspire new approaches and techniques. This work (Figure 1.5) includes a reward-based computational mechanism shedding light on biological explanation of animal action selection processes[12]. For implementation of goal-directed behaviour, a Khepera II mobile robot was used.

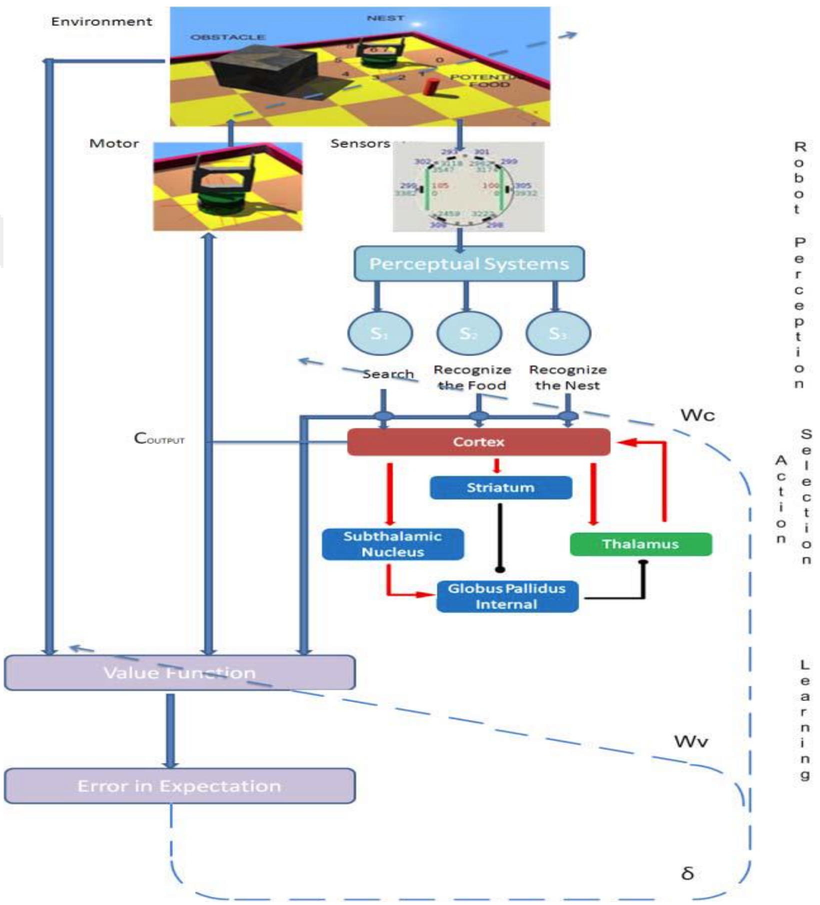


Figure 1.5 : The architecture of the model realizing goaldirected behaviour [12].

Navarro et al. investigated a neurocomputational model (Figure 1.6) of auditory-cue fear acquisition in 2012. It reveals the principles of fear conditioning and the essentials for developing adaptive, self-protective systems [13]. In order to develop adaptive self-protective systems, sensory-motor processing is a very essential aspect for understanding fear learning. This hybrid approach is efficient for exciting stimulus and learning the temporal relationship between auditory sensory cues. Detailed study of the computational mechanisms based on neural circuits in the brain supports the development of safer robots and better understanding of fear processing[13]. The hybrid approach could achieve learning the temporal relationship between auditory sensory cues and an aversive or appetitive stimulus. A neural network simulation was considered to evaluate the model and it was implemented on a robotic platform [13].

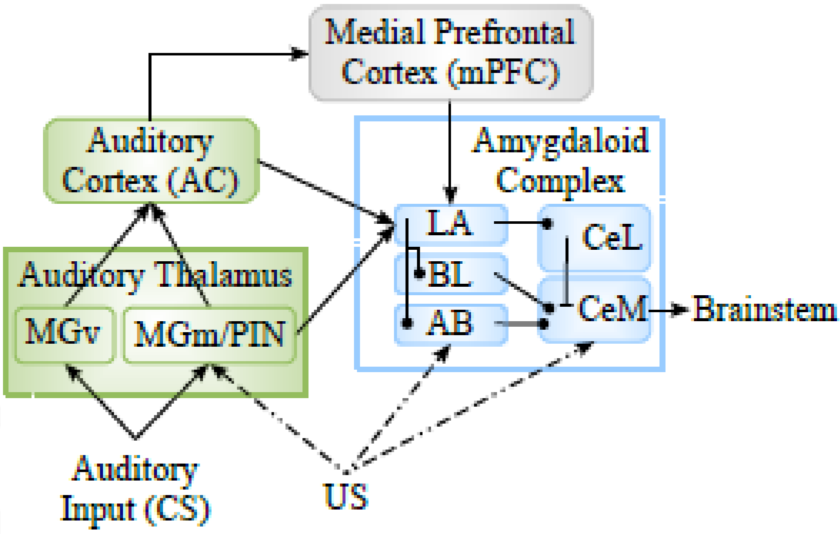


Figure 1.6 : A neurocomputational model of auditory-cue fear acquisition [13].

Richter et al. developed a dynamic neural field model inspired by human cognition in 2012 [14]. This study (Figure 1.7) provides a computational dynamic model of sensory-motor systems and realizes an action-selection procedure by coupling the dynamics between them. For behavioural organization, the theory of elementary behaviours (EBs) is a key component producing specific task sequences in this study. According to behaviour constraints and perceptual information, some behaviours like grasping and pointing can be executed by EBs' embodied dynamic neural field model. This adaptive system, including the individual sensory-motor components (EBs), yields flexible task sequences[14].

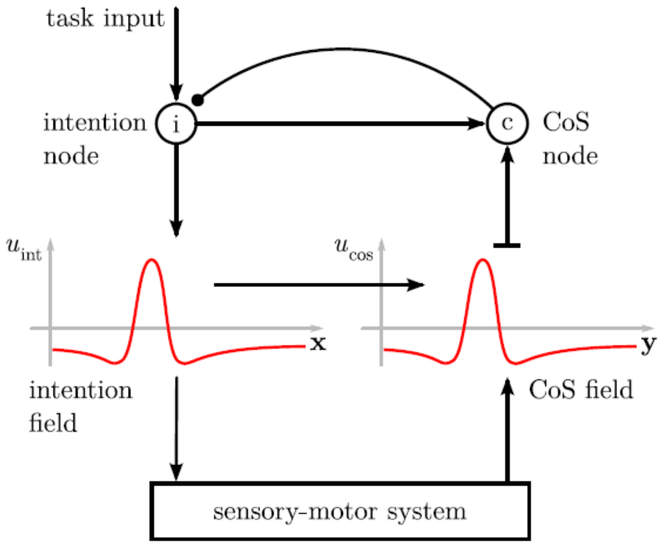


Figure 1.7 : Elementary Behaviour (EB) [14].

In 2011, Schöner et al.[15] proposed a model using DNF for scene representation. This approach (Figure 1.8) assists in the modelling of spatial cognition in humanoid robots. Their architecture, which generates scene representations, has been achieved via controlling gaze and visual attention, estimating saliences, tracking objects, and reading them into working memory. In order to process spatial information and sensory-motor structures, different dimensional DNFs are required to couple among perception and motor systems.

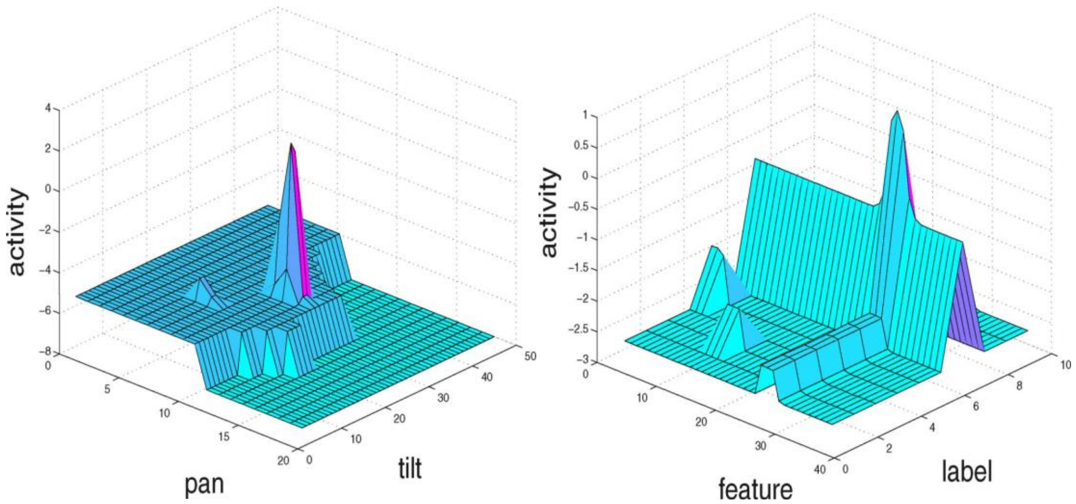


Figure 1.8 : DNF for scene representation [15].

Another important study (Figure 1.9) presented by Erlhagen et al. is a neurocognitive architecture embodying dynamic neural fields for HRI scenario in 2010 [16-19]. Their computational model, which integrates contextual cues, shared task knowledge and predicted outcomes of the human motor behaviour, allows an assistant robot to display pro-active and anticipatory behaviour for non-verbal HRI experiments. Task relevant information about action means, action goals and context is encoded into different subpopulations in the form of self-sustained activation patterns[16-19]. A coupled system of dynamic neural fields representing a distributed network with specific functionalities performs the coordination of actions and goals with the human.

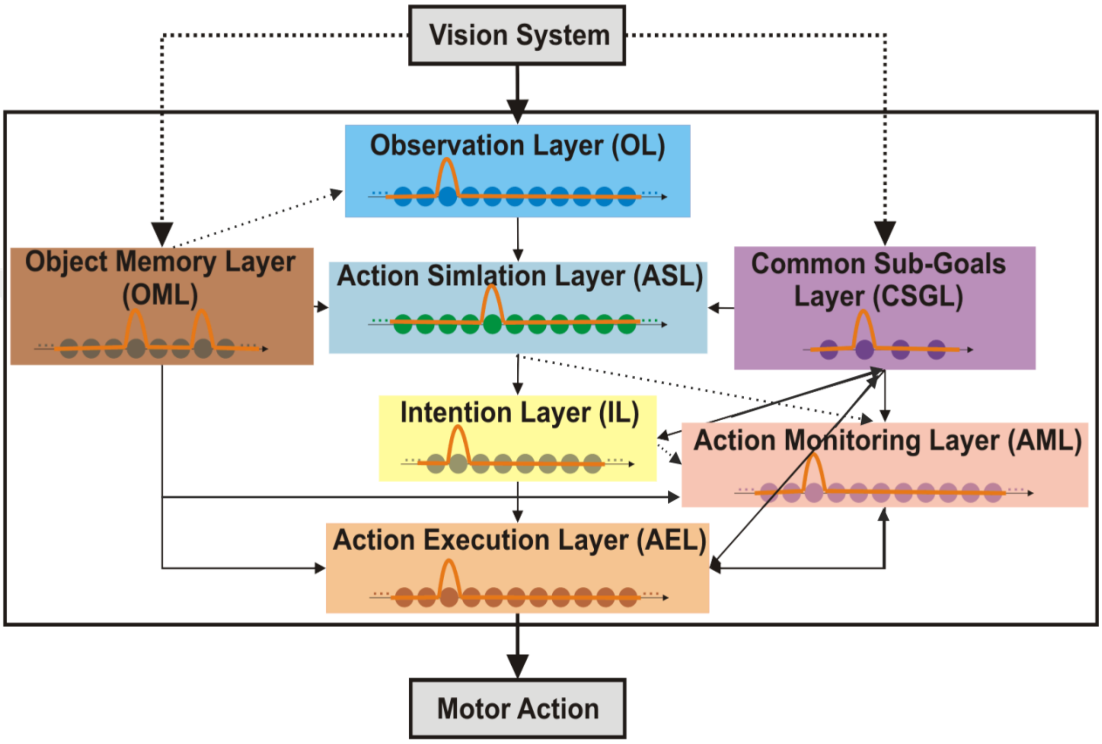


Figure 1.9 : Pro-Active Neuro Cognitive Architecture [16].

Sauser et al. [20] presented a biologically inspired approach to multimodal integration and decision-making in the human-robot interaction studies. A dynamic neural field based framework was developed so that cooperative and competitive interactions were provided by sensorimotor representations. Using this computational model, the human imitation abilities, social interactions are likely to be linked with fundamental abilities of human.

In addition, computational cognitive architectures have been developed to solve perceptual and environmental modelling problems for humanoid robots. The number of projects are rapidly increasing, and they are expected to rise as an emergent issue in the future. Francesco Rea conducted a promising study on visual perception and attention model for a humanoid robot in 2012 [21]. Furthermore, as a cognitive architecture, the brain inspired emotion recognition framework was first published as a novel study on the design principles underlying the Gabor filter based feature extraction of a human face and recognition of emotional expressions by a recurrent neural network in 2006 [22].

1.3 Description of Related Work and Problem Statement

Autonomous humanoid robots are widely used in various platforms such as health care (rehabilitation), education and domestic areas. However, their application in social areas requires an embodied computational framework incorporating highly developed cognitive skills [2]. Although the human brain naturally performs all these cognitive skills within own entity, robots come across severe difficulties due to world model and task uncertainties. It is a quite challenging issue that high level cognitive skills which are able to respond multi-modal perceptual stimuli can provide some properties having environmental awareness, ability to recognize patterns and develop a model of attention [6]. Due to deficiencies in coordination between multi-modal stimuli, modelling of the robot's perceptual environment (e.g. spatial world model or behavioural model of human(s) interacting with robot) is one of the biggest problems [23]. Therefore, major challenges in this thesis study can be divided into several sub-topics such as perceptual processing, emotional appraisal, action-selection task, episodic, procedural and working memory formations. In addition, interaction quality between human and the robot is shaped with robot's high-level cognitive abilities such as awareness and attention modelling.

For application domain, attracting and maintaining the attention of children are great challenges from the perspective of human-robot interaction (HRI) studies [3]. The interaction levels of children, which should be investigated through turn-taking interaction gameplay scenarios with a humanoid robot, vary depending on the attention model type [24]. Moreover, some conditions severely hinder their realization using HRI in socially shared environments. In hopes of resolving this issue, the proposed computational framework would enable humanoid robots to increase interaction-based attention in preschool children, such that a robot may be used as an educational or rehabilitative assistant [4].

1.4 Research Questions and Hypothesis

Testing criteria including rate of success, time of activity, number of trials, errors, reinforcements (e.g., rewards or punishments), and computational or optimization costs can be proposed to evaluate internal states of the proposed computational framework to observe the performance of interaction between a humanoid robot and the human subject [25-45]. Neuromorphologic adaptation and learning statistics of the humanoid robot's artificial brain model (computational framework) can be added to these measures as internal indicators (hidden variables).

Possible research questions (RQs) related to thesis can be offered as follows:

RQ 1: How would social interaction based on joint attention be established between a humanoid robot and human so that the robot may be used as an educational or rehabilitation assistant?

RQ 2: How does the humanoid robot achieve human like perceptual cognition, which evaluates spatio-temporal awareness that investigates correlation between pattern recognition skills, semantic memory development and selective attention model with competitive focuses under multi-modal stimuli?

RQ 3: How can the diagnosis of preschool children's (ADHD or normal group) current and past status related to interaction levels based on attention via the robot's emotional activations (or expressions) and episodic memory be retrieved by its computational framework?

RQ 4: How can attention deficiencies of preschool children be improved (or recovered) through optimal action sequences generated by the robot's behaviour selection mechanism?

Definition 1: *Focused attention* corresponds to an individual's ability to respond discretely to specific perception stimuli [24, 27].

Definition 2: Observation times of continuous and repetitive interaction behaviours are effectors of *sustained attention.* Sustained attention is defined as the ability to maintain a stable cognitive activity while these behaviours are being processed [24, 27].

Definition 3: The term *joint attention* corresponds to an individual's ability to establish a communicational link with the other (human or robot) in domain of attention.

Definition 4: The ability to explore and resolve all perceptual relations, while the individual interacts with environment and the other, is expressed as *perceptual awareness*.

According to these definitions, the focused attention level is related to recognition errors and response times of the gestures perceived. Focused attention level can be extracted from the emotional state of the humanoid robot. The sustained attention level of an individual corresponds to the maximum duration without reducing interaction performance. The interaction performance score can be evaluated by success rate (or frequency) in the sequence of events (gestures to be perceived) for a short time window (Δt). Focused and sustained attention levels are merged to represent a unified (or general) attention measurement indicator. We put forward a statement that general (unified) attention level related to interaction performance is measured by a computed reward related to reinforcement learning of the action selection progress. Thus, preschool children's interaction performance can be easily diagnosed from changes in attention level between the past and present during the experiments. If the change of improvement level in the general (unified) attention level is greater than zero, interaction based on attention is effectively achieved in preschool children using HRI. Hence, we intend to show that the current status and change of improvement level can provide an action sequence (or policy) such that the change of improvement level is greater than zero.

The following hypothesis can be tested depending on the research questions:

Hypothesis 1: If the response times and recognition errors of the stimuli decrease monotonically, the computed reward related to emotional state increases and interaction based on focused attention increases between the humanoid robot and preschool children.

Hypothesis 2: If the success rate (or frequency) in the sequence of events (perceived gestures) within a short time window (Δt) increases, the interaction performance score increases, and interaction based on sustained attention increases between humanoid robot and preschool children.

In the literature, presented standard solutions have not thoroughly grappled with these problems. When investigating from the computational intelligence, computer science and engineering viewpoint, standard deterministic behaviour selection mechanisms with ordinary supervised or reinforcement learning algorithms have not achieved the expected goals. Especially, computational modelling of human's cognitive skills with biological plausible artificial neural mechanisms (e.g. networks of spiking neurons, dynamic neural fields and neural mass models) concepts are still uncovered philosophical facts for the robotics.

On the other hand, the proposed novel solution could be a suitable candidate for verifying the hypotheses that humanoid robot embodied computational cognitive framework could improve the attention-based interaction of preschool children. In addition, the network of spiking neurons helps to realize adaptive and emergent behaviours by neural mass models including population dynamics. This phenomenon, which is also supported by field-like dynamics (e.g. dynamic neural fields), can be embodied in cognitive architecture of the humanoid robot. Proposed novel neural structure can encode spatio-temporal relations or features of the dynamic interaction between robot and child. Episodic memory formation which can store past events (e.g. interaction history) involves measuring or detection of attention level of child during interaction. To improve a child's attention, humanoid robot's emotional activity giving rewards for optimal action selection is a key element so that attention level of preschool child can be boosted via parallel task processing in neural structure of action selection mechanism while it is slightly diminishing. Therefore, the presently proposed computational limbic system framework, realizing neuromorphologic plasticity (adaptation), may provide a novel solution to ADHD issues. For verification, the described hypotheses are tested via scenarios supported by turn-taking interaction gameplays for preschool children.

1.5 Contribution and Statement of Novelty

In the current study, we propose a brain-inspired computational framework of embodied cognitive functions for a humanoid robot, to improve the human robot interaction based on joint attention. Therefore, it is essential to investigate the biological nature of cognitive systems from the viewpoint of a humanoid robot.

In chapter 3, a computational perception system inspired by human brain's sensory regions is developed for a humanoid robot that can easily communicate with its environment. According to research questions (RQ 1 and RQ 2) depicted in section 1.4, this study investigates joint attention, perceptual awareness and spatio-temporal perceptual cognition for the human-robot interaction.

In chapter 4, the other major aim of the study that covers research questions (RQ 3 and RQ 4) and hypotheses (H1 and H2) depicted in section 1.4 seeks to build computational limbic system including the modelling of emotional responses and formation of episodic memory. In addition, the proposed system involves an action-selection mechanism based on a reward-based learning procedure. This is achieved by combining different heuristics with machine learning techniques to obtain solutions to a range of problems. The proposed cognitive architecture employs a DNF model based on field dynamics of a biologically plausible neural structure (e.g., cortical tissue). The effectiveness of the model is compared with a neural mass model utilizing the population dynamics of biological neurons.

1.6 Organization of the Thesis

The thesis is structured as follows: section 2 provides preliminary background information about the methods and computational tools used in the study; section 3 provides detailed information about the proposed computational perception system introducing visual cortex, temporal and parietal cortices with revealing experimental results; section 4 lays out the design principles of the proposed computational limbic system architecture that produces emotional responses, episodic memory, and motivational effects on the behaviour selection mechanism with performance evaluation analysis; finally, section 5 provides a discussion of conclusions that can be drawn from the current findings in the context of previous research, and presents several possibilities for future research.

2. BACKGROUND

In this chapter, reference studies are presented to build a theoretical basis of the study carried out in this thesis. These studies are listed under three main topics. In order to implement a bio-inspired design in the solution, the first topic provides some anatomical evidence and basic biophysical knowledge. The second topic introduces preliminary mathematical models and some numerical methods that are used in computational mechanisms of the architecture. Finally, last topic depicts information about learning algorithms so that neuromorphological adaptation and neural plasticity are realized in components of the architecture.

2.1 Biophysical and Anatomical Evidence

In nature, cognitive functions are controlled by cortical regions and limbic system in the human brain [6]. The limbic system including the amygdala, hypothalamus, hippocampus, and basal-ganglia; regulates the behavioural and cognitive abilities of humans [6]. While basal-ganglia selects a behaviour (e.g. sequence of actions), emotional responses produced in amygdala give reinforcement effect to it. As the past events, hippocampal activities related to formation of episodic (e.g. long-term) memory may contribute to realizing these processes.

Anatomical structure of cerebral cortex includes two main cortical structures called as frontal and posterior parts. Cognitive functions related to perception skills are involved in posterior part of the cerebral cortex [46-58]. This region is divided into three sub-regions called as occipital, parietal and temporal lobes. Occipital lobe which resides in regions of primary visual cortex realizes post feature extraction on visual stimuli. Temporal lobe involves in pattern recognition on visual and auditory stimuli. Parietal lobe which accepts visual and somatosensory stimuli is responsible from spatial perception [23, 46, 59-71].

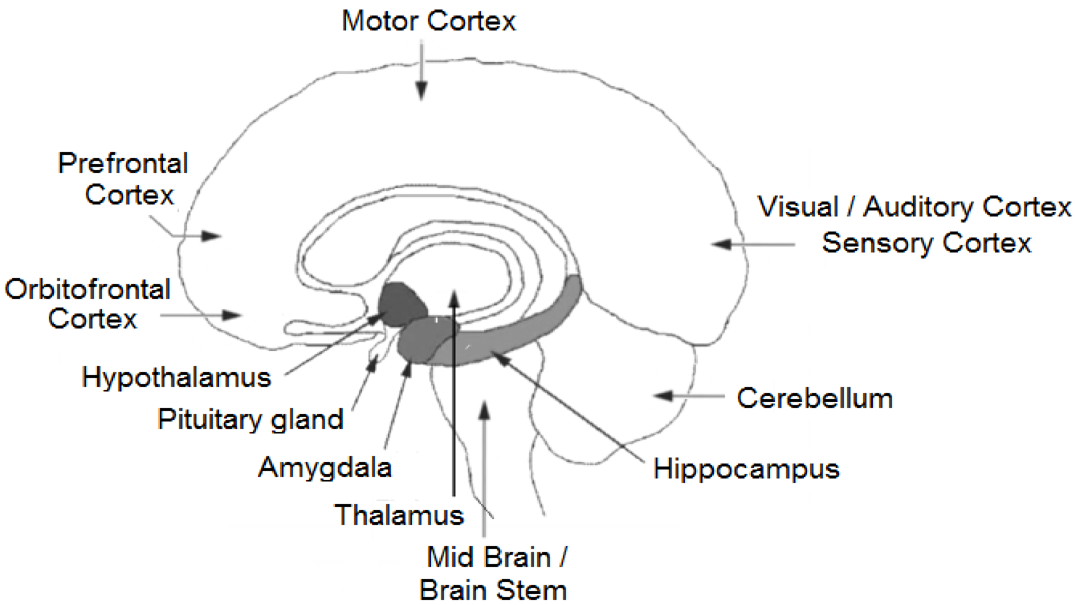


Figure 2.1 : Human brain cortical zones [6].

Cognitive functions related to reasoning, planning and working memory skills are involved in prefrontal cortex which is a part of frontal lobe of the cerebral cortex. This region is divided into four sub-cortical areas including dorsolateral, ventrolateral, anterior and medial prefrontal regions. Dorsolateral and ventrolateral prefrontal cortices realize spatial and temporal reasoning tasks respectively. Anterior prefrontal cortex (or Brodmann Area 10) performs emotional reasoning tasks. Medial prefrontal cortex including orbitofrontal cortex involves in working memory and meta-cognition [46].

2.2 Mathematical Background for Computational Design

In this section, background information of computational mechanisms in a computational neural tissue with multiple dynamics is briefly introduced. Our proposed structure for each component (region of limbic system) is based on three computational domains. The dynamics used in this structure are listed as spiking neurons, neural mass (e.g. neural population) and dynamic neural field.

Unification of these dynamics with soft computing techniques provides a computational neural tissue which realizes cognitive skills of specific limbic system regions such as basal-ganglia, amygdala, hypothalamus and hippocampus.

2.2.1 Spiking Neurons and Networks

Due to the nature of the human brain, utilizing neural computing approaches is more likely coherent with purpose of the thesis. Different types of distributed computing cells (artificial neurons) are studied to construct a computational framework of a huge nervous system for robots. Classical artificial neural networks usually employ McCulloch-Pitts [72] neuron model for solution of engineering problems whereas mathematical models of biologically plausible computational neurons like spiking neural models (e.g., Integrate & Fire, Hodgin-Huxley, Izhikevich models) [73, 74] are also available. In 2003, Izhikevich model emerging from Hodgin-Huxley model has been introduced which can effectively represent most of the behaviours of neural activation.

From the two models (Izhikevich and Hodgkin-Huxley), different spiking behaviours can be observed such as tonic spiking, phasic spiking, tonic bursting, phasic bursting, spike latency, subthreshold oscillations, resonator, integrator, rebound spike/burst, inhibition-induced spiking/bursting.

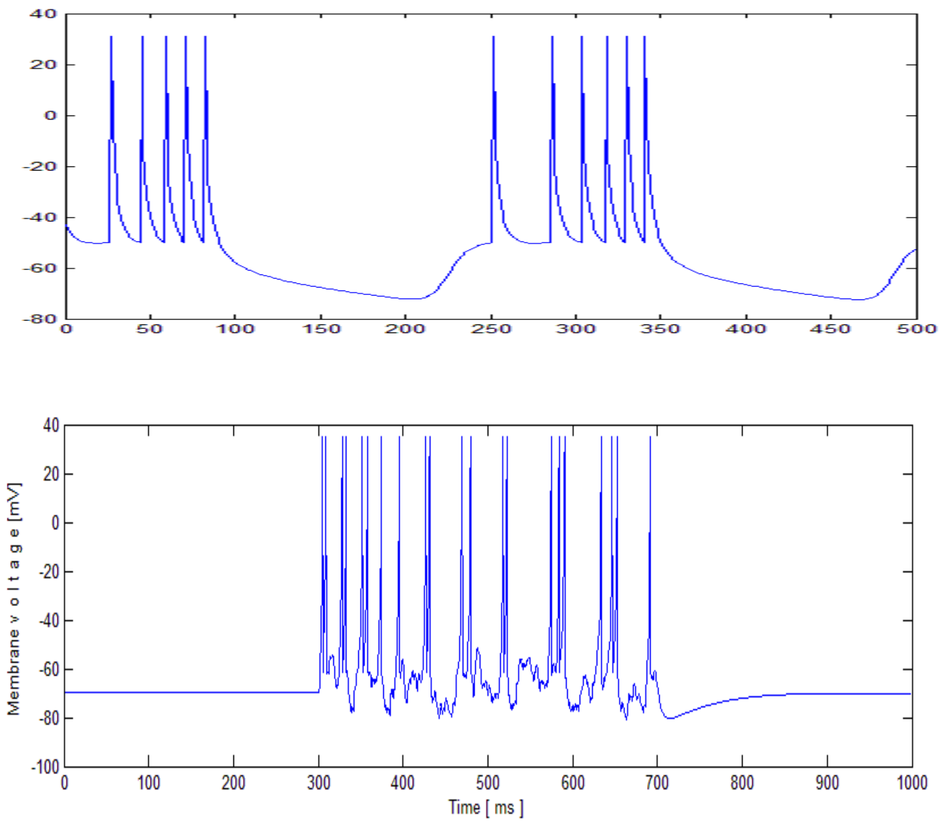


Figure 2.2 : Spiking neural activities observed from Izhikevich model.

Neural cells can be represented as nonlinear circuits with a capacitor acting like an integrator. In addition to this, stochastic and chaotic behaviours like dynamic attractions are taken into consideration [73, 74]. The conductance-based models can be generally expressed by

$$C\frac{dV_j}{dt} = \sum_i g_i \phi_i (E_i - V_j) + I_{ext} \tag{2.1}$$

Where I_{ext} represents the external input current. Also, V_j depicts the j^{th} neuron's membrane potential, with a capacitance coefficient C. Potential E_i indicates reversal potentials related to their ion channels. Their conductance parameters g_i and reversal potentials E_i help to generate ion currents through gate variables ϕ_i , which are computed by ordinary differential equations.

$$I_{ion} = \sum_i g_i \phi_i (E_i - V_j) = I_{Na} + I_K + I_{Ca} - I_L \tag{2.2}$$

$$I_{Na} = g_{Na} m^3 h \left(V_j - E_{Na}\right) \tag{2.3}$$

$$I_K = g_K n^4 \left(V_j - E_K\right) \tag{2.4}$$

$$I_{Ca} = g_{Ca} \left(V_j - E_{Ca}\right) \tag{2.5}$$

The current term I_{ion} represents ion channels and external input currents respectively. Different ion channels I_{Na}, I_K, I_{Ca}, I_L show sodium, potasium, calcium and leakage currents. Their conductance parameters g_{Na}, g_K, g_{Ca} and reversal potentials E_{Na}, E_K, E_{Ca} help to generate ion currents via $\mathrm{p} = \{\mathrm{n}, \mathrm{m}, \mathrm{h}\}$ gate variables which is computed by the following differential equation [73].

$$\frac{dp}{dt} = (1 - p)\alpha_p(V_j) + p.\beta_p(V_j) \tag{2.6}$$

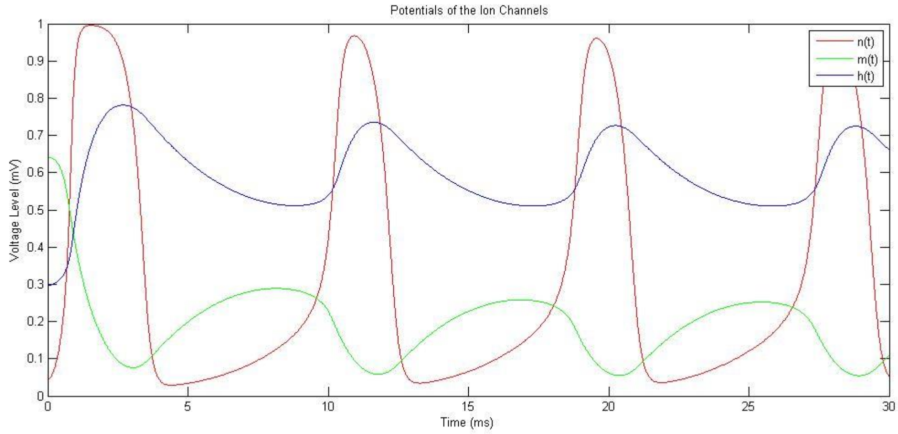


Figure 2.3 : Spiking neural activity observed from Hodgkin-Huxley model [73].

In figure 2.3, variations of membrane potentials and fired spikes are shown. Due to the computational complexity of conductance-based models, the Izhikevich model [74], which is more basic and efficient, is preferred in developing generic neural tissue (structure). It is composed of two simple differential equations.

$$\frac{dV_j}{dt} = 0{,}04{V_j}^2 + 5V_j + 140 - u + I_{ext} \tag{2.7}$$

$$\frac{du}{dt} = a(bV_j - u) \tag{2.8}$$

where V_j is the membrane potential of the j^{th} neuron and u is the recovery variable. External currents including synaptic input are applied to I_{ext}. However there is a certain spike threshold, which causes V_j to reset to a potential level.

if $V_j \geq 30$ mV
Then$V_j = c; \quad u = u + d;$

Also the recovery variable u is updated by this thresholding process. The system parameters are expressed as a, b, c, and d, so that different spike behaviours in the cortical region neurons can be obtained.

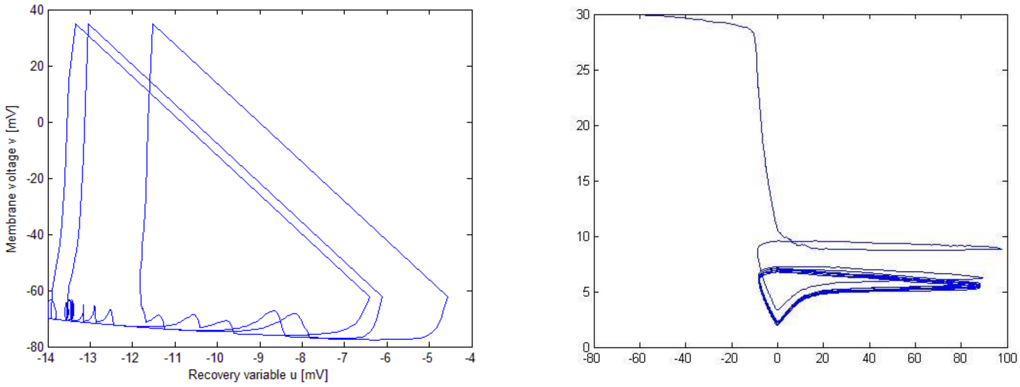


Figure 2.4 : Membrane potential of a specific neuron and its dynamic behavior (phase portrait).

The cell's updated equation, familiar and compatible to the Hudgkin-Huxley and the Izhikevich models, is based on the conductance model depicted in the equation (2.19). Thus, the model can exhibit some complex nonlinear system behaviors including bifurcation, phasing, chattering, tonic, bursting, integrator/resonator, periodic oscillator, inhibitation, and adaptive spiking [74]. A circuit-based model representation requires additional parameters. Extension of the two models can be realized by modifying the external input current I_{ext} , to include I_{syn}, I_{app}, and I_{stoc}.

$$I_{ext} = I_{syn} + I_{app} + I_{stoc} \tag{2.9}$$

The term I_{syn} defines interconnection currents between neurons. The current I_{app} is produced by external stimuli. As a bias or disturbance current, I_{stoc} is a stochastic noise current generated by a function of the Wiener process.

$$I_{syn} = -\sum_{j} W_{ij} g_j(t)(E_i - V_j) \tag{2.10}$$

$$I_{app} = -\sum_{k} \omega_{kj} g_k(t)(E_k - V_x) \tag{2.11}$$

The weight matrix W_{ij} defines interconnectional strengths between neurons and the matrix ω_{kj} depicts input strenghts of the network coming from external stimuli. The conductance vectors $g_j(t)$, $g_k(t)$ are defined as gating variables of inter-neurons and input to the network respectively. Potentials E_i, E_k indicate reversal potentials related to inter-neurons and input flow.

$$\frac{dg_k}{dt} = \left(1 - \frac{\Delta t}{\tau}\right) g_k \tag{2.12}$$

$$g_k(t) \leftarrow g_k(t) + 1, \qquad if \;\; r_k(t) < f_{rate}\Delta t \tag{2.13}$$

The parameters are set as $\tau = 10\ ms$ and $r_k(t) \in [0, 1]$.

2.2.2 Neural Masses (Population Dynamics)

The space or cloud of spiking neurons is driven by firing rate models of a neural population. Besides main neuron pool, there can be some kinds of sub-populations called excitatory and inhibitory populations. The general form of neural population density can be interpreted by Jansen-Rit's neural mass model equations [75]. There is a very close relationship between the signal relay from population density of a neural mass and electroencephalography (EEG) activity [76].

$$h^{e,i} = H^{e,i} \frac{t}{\tau} \exp\left(-\frac{t}{\tau}\right) \qquad t \geq 0 \tag{2.14}$$

The term$h^{e,i}$ is the impulse response function, depending on the excitator (h^e) and inhibitor (h^i) in the neural population. Parameters τ, H are time constant and the amplitude of the impulse response function respectively. The exogenous term *I* is the mean ensemble firing rate of the presynaptic excitatory input which is passed into the computational model of the neural mass.

$$y_1 = h^e \otimes (f(W^{exc} y) + I) \tag{2.15}$$

$$y_2 = h^i \otimes f(W^{inh} y) \tag{2.16}$$

The connection matrices W^{exc} and W^{inh} define excitatory and inhibitory weights of the computational model of the neural mass. The special operator $\otimes$ stands for a convolution integral.

$$(f \otimes g)(t) = \int_0^t f(\tau) g(t - \tau) d\tau = \int_0^t f(t - \tau) g(\tau) d\tau \tag{2.17}$$

$$f(x) = \frac{1}{1 + e^{-\alpha x}} \tag{2.18}$$

The function f is a sigmoidal activation function. Post-synaptic output response mean potential y is produced by pre-synaptic excitatory and inhibitory mean potentials $y_{1,2}$ as shown in equation (2.19).

$$y = h^e \otimes f(y_1 - y_2) \tag{2.19}$$

The equation (2.19) gives general formulation of a neural mass (neural population) response as time varying mean synaptic potentials. Also this equation, representing overall neural activation of a neural population, can be rewritten in a lumped form. The corresponding second order differential equation is:

$$\ddot{y} = H^e \frac{t}{\tau} f(y_1 - y_2) - 2\frac{t}{\tau}\dot{y} - \frac{t^2}{\tau^2} y \tag{2.20}$$

The signal, which stimulates a neural mass, is generated by contribution of mean (synaptic density) rate coding, including firing latencies (delays) and spiking counts.

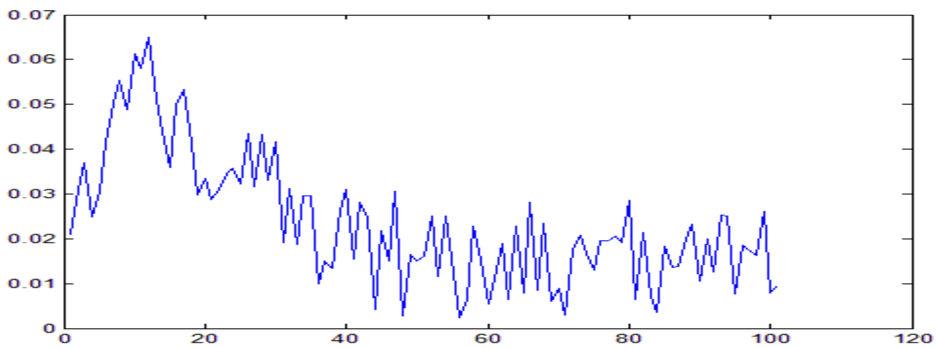


Figure 2.5 : The time varying avarage mean synaptic potential of the neural population.

In figure 2.5, activation of a neural population is presented as average mean synaptic potentials. The signal which stimulates a neural mass is generated by contribution of mean (synaptic density) rate coding including firing latencies (delays) and spiking counts of a neural population.

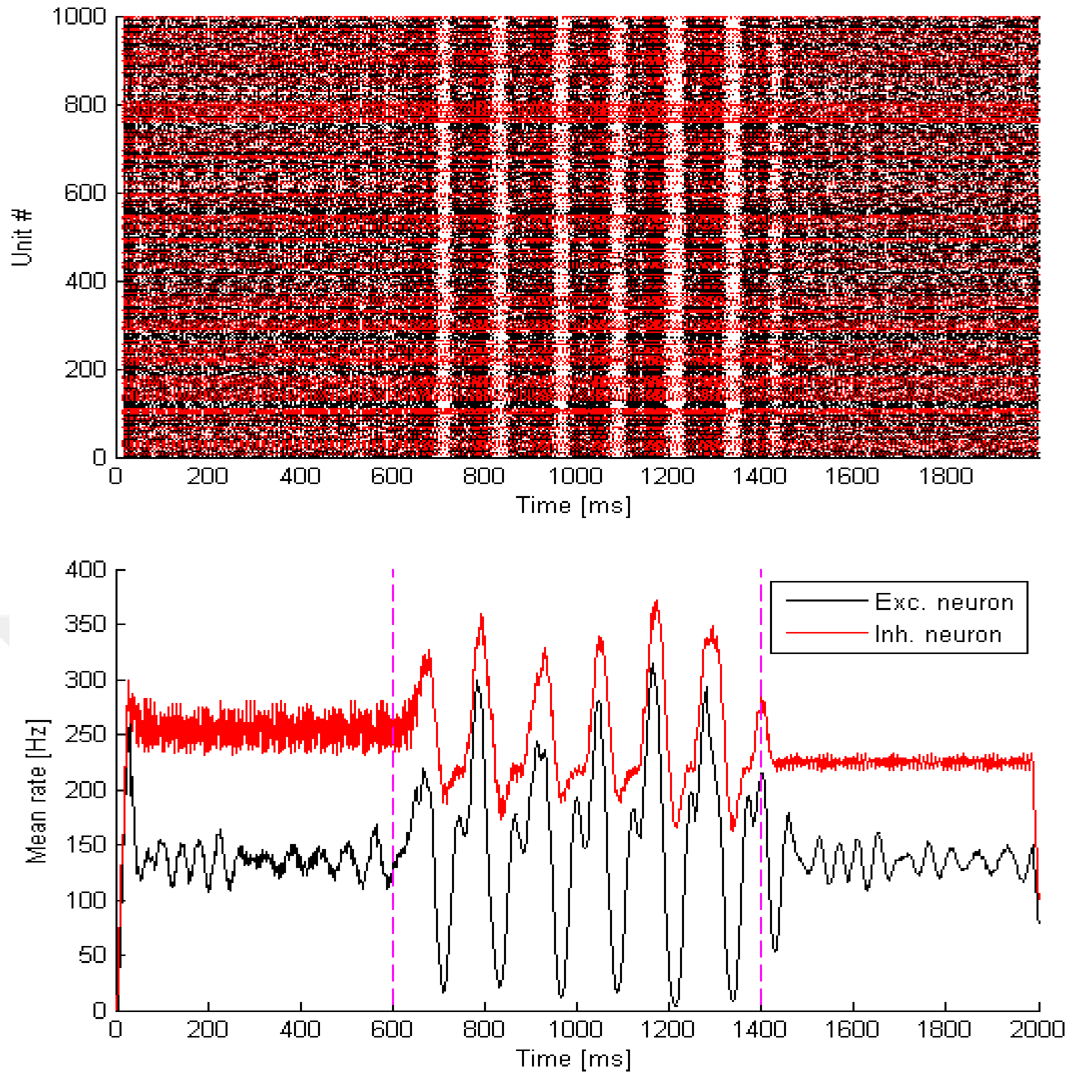


Figure 2.6 : The time varying avarage mean synaptic potential of the neural population.

2.2.3 Dynamic Neural Fields

Dynamic neural field (DNF) theory is based on Amari equations [77], which visualize mental activities similar to functional magnetic resonance imaging (fMRI). DNF involves in field or wave like neural activity rather than a circuit based simple neural network architecture.

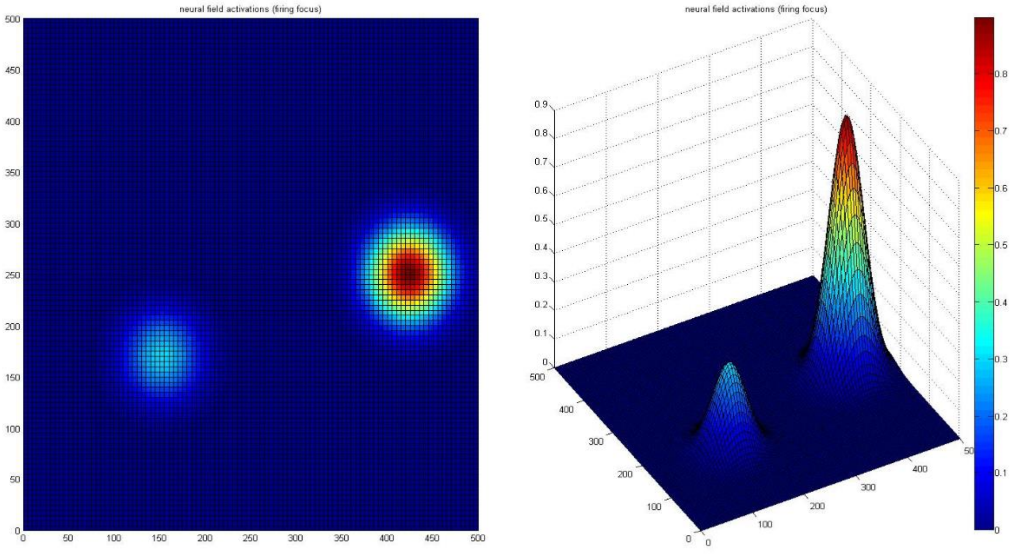


Figure 2.7 : Activities of the neural field.

$$\frac{d}{dt}U_i(x,t) = -U_i(x,t) + \int w_i(\ell).f\big(U_i(x-\ell,t-\tau)\big)d\ell + \int S_j(x,y).I_d(y,t)dy + h \tag{2.21}$$

where $\ell = x - x^{'}$ is a spatial distance from the mean of cortical field. A weight matrix $w_i(\ell)$, which is a function of the spatial information distance, includes connection strengths of the synaptic activation inside the field $U_i(x,t)$. The function f is a sigmoidal activation function. The parameter h corresponds to the bias. External effects can be realized in the exogenous connection matrix $S_j(x,y)$ and exogenous input field activity $I_d(y,t)$.

$$w_i(\ell) = w_{exc}.e^{-\ell^2/2.\sigma_{exc}^2} - w_{inh}.e^{-\ell^2/2.\sigma_{inh}^2} \tag{2.22}$$

$$S_j(x,y) = s_j.e^{-(x-y)^2/2.\sigma_j^2} \tag{2.23}$$

where w_{exc} and w_{inh} are excitation and inhibition strengths, respectively. As parallel and distributed computing blocks, the field dynamics of the computational neural tissue improves the model employing biophysical, meaningful spiking neuron populations and neural masses.

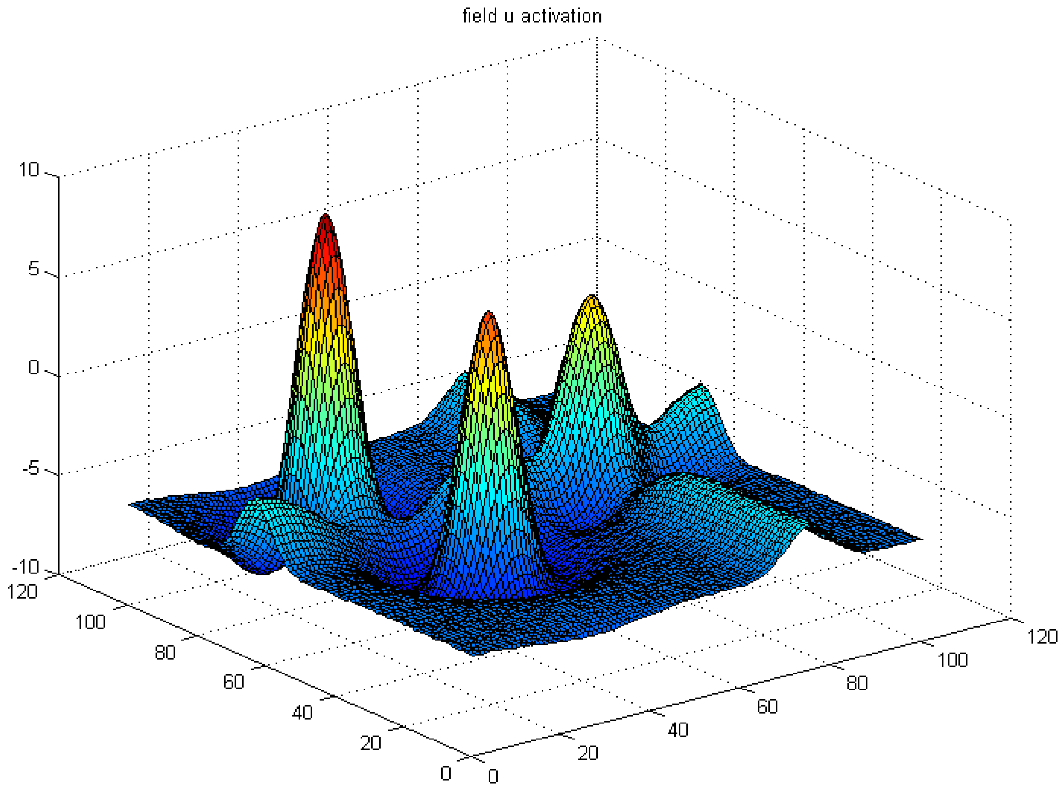


Figure 2.8 : Excitation and inhibitation effects on activities of the neural field.

2.3 Unifying Neural Dynamics

Neural approaches are often used in robotic research. Naturally, computational modelling of cognitive and mental processes in the human brain, for application in humanoid robots, requires high-density neural structures. Assembling small groups of cellular computing units (e.g., neurons) produces larger complex structures (e.g., cortical regions). Their connection topologies allow brain activities with chaotic dynamic characteristics to be computationally reproduced for artificial brain frameworks. Therefore, higher-order neural structures, cortical field networks, are considered as the generic building blocks of computational architecture.

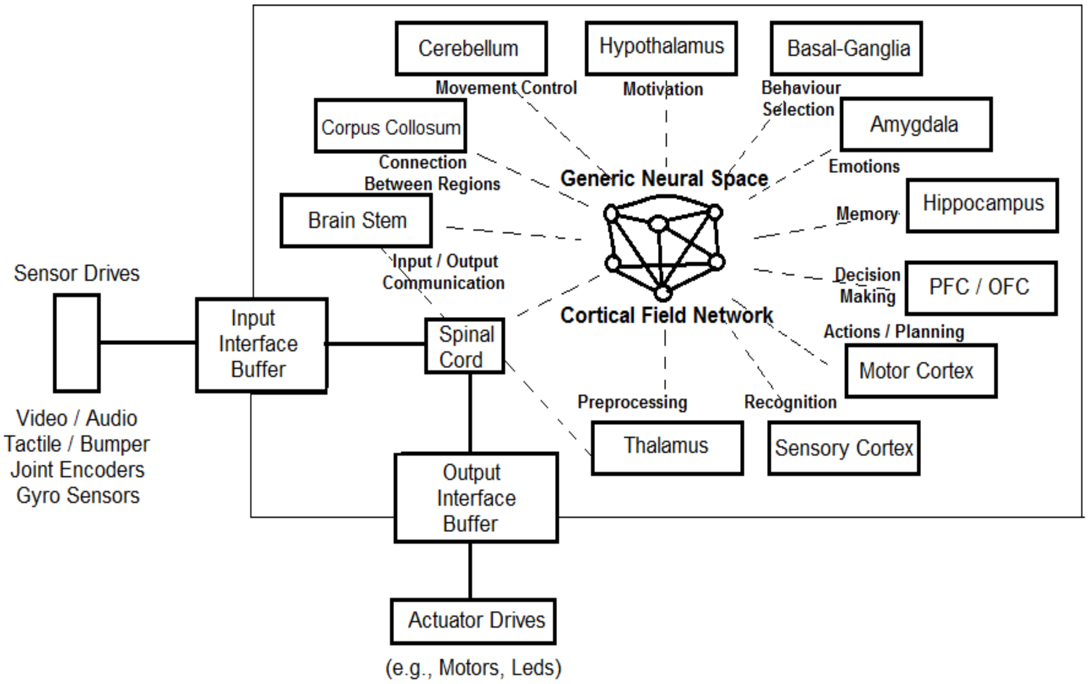


Figure 2.9 : Specialization of generic neural structure to cortical regions.

Each region of the proposed framework for humanoid robot is composed of computational neural models including multiple dynamics such as neuron, mass (population) and field domains. Every neuron, which has continuous membrane potentials in the space of the neuron cloud, produces different type spike patterns. Then population dynamics driven by neural mass equation provide information flow in the computational neural tissue. The proposed model, employing a group of computational neural tissues, exhibits certain stochastic and nonlinear dynamic properties; including chaotic behaviours, multimodal or strange attractors, and chattering. As parallel and distributed computing blocks, the field dynamics of the computational neural tissue improves the model, which employs biophysically meaningful spiking neuron populations and neural masses.

The computational mechanism used in the proposed brain-inspired cognitive architecture is influenced by field dynamics of the neural model. Additionally, population dynamics of the artificial neurons is investigated in this architecture for comparison purposes. In this study, we only concentrate on specific modules (e.g. feature extraction, cognitive perception, amygdala, hippocampus and basal-ganglia) of the general architecture. To reduce complexity, the effects of some modules are ignored or simplified.

2.4 Learning Algorithms and Neural Plasticity

The first meaningful explanation of learning algorithms was proposed by Donald O. Hebb in 1949 [78]. The Hebbian learning paradigm takes into consideration synaptic strengths (weights) between the neurons. In biological systems, neurons exhibit spiking patterns, where higher-level structure representation of the computational neural dynamics (e.g., neural field, neural mass and neural spikes) propagates population activity signals (e.g., EEG) and wave packets travelling in the cortical sheet (e.g., neural field). The relationship between the pre- and postsynaptic activities are involved in synaptic adaptation and neural plasticity. Weight updating is realized according to Hebbian plasticity. In addition, the firing rate of the population activities can be affected by the weight modification rule. Then we write the generalized learning rule for $\Delta\omega_{ij}$ as:

$$\Delta\omega_{ij} = \omega_{ij}(t+1) - \omega_{ij}(t) = -\alpha(t)\frac{\partial E}{\partial \omega_{ij}} \tag{2.24}$$

where term E is a cost function. The effect of learning rate $\alpha(t)$ as an optimization factor is to determine convergence speed during the training process.

The basal ganglia is associated with procedural memory for the action selection mechanism [46]. According to reinforcement learning procedure, emotional model changes emotional states [6]. The major benefit of reinforcement learning [79] is that the agent has a goal-directed nature which acquires rewards from interaction with its environment. The update term is obtained by temporal difference equation.

Pseudo Algorithm: Reinforcement Learning [79]
***initialize** value**,** weight and reward*
***foreach** iteration*
calculate temporal difference (TD) = reward + discount x posterior value – prior value
dw = computing weight modification (TD)
posterior weight = update synaptic weight (prior weight, dw)
***until** convergence occurs*
end

The hippocampus has remarkable functions for semantic and episodic memories, which are classified as declarative and long-term memory. The neural activation in the hippocampus involves in unsupervised Hebbian learning [46]. To realize adaptation (or neural plasticity), the self-organizing map algorithm might be associated to learning progress in the hippocampus. The self-organizing map algorithm [80], which is updated utilizing unsupervised learning, allows to cluster memory patterns according to the familiarity of memory activations.

```
Unsupervised Learning Algorithm: Self-Organizing Map [80]
initialize network (map)
foreach iteration
        locate input pattern into map
        calculate the best matching unit (bmu) as winner = input pattern – prior weight
        determine range of effectiveness (Radius of neigborhood)
        if distance(neuron - winner) < range
                dw = computing weight modification (winner)
        posterior weight = update synaptic weight (prior weight, dw)
        endif
until convergence occurs
end
```

2.5 Experimental Setup

In this study, the main experiment platform is a Bioloid humanoid robot of Robotis (Figure 2.10) [81]. Bioloid is composed of 18 smart servo actuators (AX-12A), several peripheral body sensors (e.g. IR transmitters, 2 axis gyro, proximity sensor for distance measurement) and a main controller CM530 containing Arm Cortex based CPU, external I/O ports. In order to perform visual and audio based perceptual processes, humanoid robot is supported with Microsoft’s Xbox Kinect RGB-D camera mounted head as an additional sensory equipment [82].

Figure 2.10 : Humanoid robot partner: Bioloid with Kinect mounted head.

Computational workload of system architecture is hosted in a laptop PC. Brief specifications of PC include quadcore intel i7 cpu @3,9 Ghz with 8 MB cache, 32 GB DDR3 ram @1600 MHz, 4GB graphics card and 1 TB 7200 rpm HDD storage. In order to control, connections to humanoid robot can be realized by Bluetooth or USB ports. We mostly preferred USB connection in the experiments.

2.6 Software Infastructure

The computational limbic system framework for a humanoid robot was modelled, simulated, and tested in Matlab [83] programming environment. There is a software development kit (SDK) for bioloid robot platform. For communication between hardware of humanoid robot and SDK, firmware of bioloid robot platform is updated before the experiments. The developed program is supported by a graphical user interface (GUI) in a window-based format. Due to the large-scale synaptic transactions, the processes to be performed are parallelized using the parallel programming toolbox. For faster computation, all matrix operations were realized utilizing GPU array-based acceleration on sparsed matrices.

Figure 2.11 : Captured skeletons for gesture detection and recognition.

3. COMPUTATIONAL COGNITIVE PERCEPTION SYSTEM

3.1 Motivation

Humans have powerful communication abilities to interact with their social environment. However, people having attention disorders (also including children, elders, patients and people having disabilities) need more assistive social cues during social interaction. There are many social robot platforms which are widely used in recent years so that life standards of these people are increased. To achieve better social interaction between human and robot, neurocognitive models, which are capable of continuously learning present adaptive solutions for developmental and social robotics can be employed. In daily life, as a personal assistant related to educational and rehabilitation purposes, humanoid robots with embodied cognitive skills can be used to support individuals struggling to interact with their social environment[1, 5]. In order to realize them, the humanoid robot should have a human like perception system which requires spatio-temporal cognitive perception skills to interpret human's behavioural activity and establish joint attention with human in a shared workspace. The purpose of this study is to establish social interaction based on perceptual awareness and joint attention between human and robot.

3.2 Evaluation of the Work and the Methods

To model social environment, a humanoid robot should evaluate its perceptual cognition. However, problems in coordination between multi-modal perceptual stimuli complicates the modelling of the robot's spatial environment and human's behavioural activities during interaction with the robot. Also perceptual cognition of the robot is shaped with its attention model as a high level cognitive ability. From the viewpoint of developmental and social robotics, establishing environmental awareness, which is extracted from robot's attention model may be a great challenge to realize efficient social interaction between human and robot.

In this section, background information related to the study is elaboratively introduced. Our proposed solution including a cognitive perception system for a humanoid robot, provides a computational framework, inspired from posterior part of cerebral cortex in the human brain. Therefore, biophysical and anatomical structure should be presented briefly. Then computational methods to be used are introduced in detail. In our proposed system architecture, several machine learning method shave been employed such as naïve Bayes, k-nearest neighbours (k-NN), decision tree, support vector machine (SVM), feedforward neural network (multi-layer perceptron (MLP)) and convolutional neural network (CNN or ConvNet). Comparison of these methods depicts the effectiveness of the computational cognitive perception system, which realizes related perceptual cognitive skills for a humanoid robot.

Naive Bayes is a basic machine learning method which classifies the problem samples (vectors of feature values) and assigns them to the class labels [84]. Although there exist a family of algorithms based on a common principle, there is not a unique algorithm for training such classifiers. Generally, naive Bayes classifiers are trained very efficiently via a supervised learning approach. For some kind of probability models in the naive Bayes classifier algorithms, parameter estimation mechanism uses the method of maximum likelihood in many practical applications [85]. The k-nearest neighbours (k-NN) model is a non-parametric algorithm, which is utilized for classification and regression in pattern recognition applications [86]. The source data of the algorithm contains the k closest training samples in the feature space [87]. For classification case, an instance to be assigned to a class as an output is labelled by the most vote of its k nearest neighbours. In case of regression applications, the output is calculated such that the property value is the average of the values of its k nearest neighbors. Decision tree provides a decision making mechanism organized as a tree-like structured model of decisions and it includes prospective outcomes, costs and utility values [88]. General form of the algorithm consists of many conditional control statements. Decision trees are widely utilized not only for classification problems but also for regression problems in various machine learning applications. As a decision support system, specific implementation cases may be decision analysis, operations research or strategic planning [89]. Usually, these algorithms are trained via the supervised learning approach. As a useful machine learning tool, the support vector machine (SVM) is a supervised learning methodology. SVM analyses a set of training sample data including categorical labels and the feature vectors associated with these labels so that the training algorithm generates a model used for classification and regression analysis [90]. Trained model which seperates groups of sample data identifies the given new sample data and assigns the categorical label associated with this data. In addition, SVM algorithm can be customized using with kernel functions such as linear or nonlinear [91].The convolutional neural networks (CNN, or ConvNet) are considered as a sub-branch of deep learning method under the machine learning algorithms. Working principle of ConvNet is based on biological processes which are involved in the visual cortex in the human brain [92]. ConvNet consists of several cascaded layers. Actually, it deals with two main parts such as feature learning layers and classification layers. ConvNet may include many feature learning layers which are stacked form of [convolution layer, ReLU, max pooling layer]. Classification layers include sub-layers such as fully connected layer and soft max layer. Usually, ConvNets are trained by stochastic gradient descent (SDG) algorithm which is a supervised learning method [93].

In this study, three-tupled (human, robot and environmental model) fold relation of social interaction is investigated through proposed scenarios in the light of research questions 1 and 2 in section 1.4. In order to verify hypotheses, some performance measures like convergence of optimization costs, success rates, response times of focusing, rate of motivation level, recognition performances (e.g. number of trials, learning errors) are investigated as testing criteria related to problems of perceptual awareness and joint attention during the interaction between human, robot and environment shown in figure 3.1. Neuromorphologic adaptation and learning statistics of the humanoid robot’s artificial brain model added to these criteria as auxiliary indicators [27].

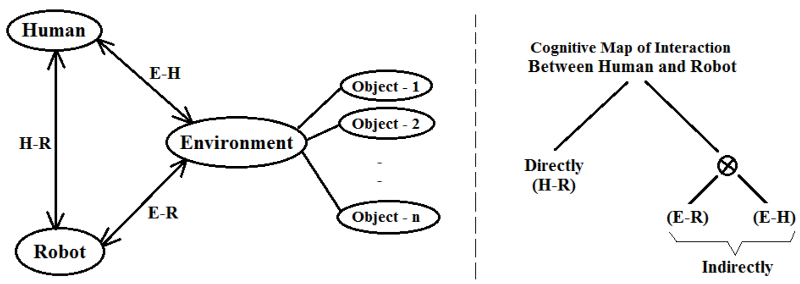


Figure 3.1 : Cognitive map of social interaction between human and robot.

Proposed novel structure could encode spatio-temporal relations or features of the dynamic interaction between robot and world model. To improve a robot's world model, its attention model extracted from high level perceptual processing is a key element for measuring or detection of spatio-temporal awareness level of robot during interaction with its environment [27]. Therefore, the presently proposed computational cognitive perception system, realizing neuromorphologic plasticity (adaptation), may provide a novel solution to environmental awareness and attention modelling issues for a humanoid robot [94].

3.3 Computational Framework of Cognitive Perception System

In our proposed cognitive framework (Figure 3.2), the perception accepting multi-modal input data streams (e.g. visual, auditory and somatosensory) is one of the most critical functions. In this section, the computational framework of brain inspired cognitive perception system is described so that it composes of the perceptual model of the robot interacting with environment and humans [6, 46]. This architecture related to cognitive perception is composed of two major cortical regions, namely thalamus and sensory cortex which are in posterior part of the cerebral cortex. Also these cortical regions have their own specialized sub computational modules for visual perception, auditory perception and somatosensory (body) perception. Before cognitive perception processes, some feature extraction tasks realizing segmentation, edge detection and filtering (i.e. Gabor filter [95]) are performed as data pre-processing activities. After these preliminary progress are completed, higher level cognitive modelling is realized by perceptual awareness and attention modelling for a humanoid robot so that social interaction skills such as human-like communication between robots and humans are established [69].

Perceptual cognition mechanism includes abilities such as spatial cognition and temporal cognition. The spatial cognition deals with environmental (workspace) awareness which involves spatial encoding (e.g. locations, orientations, distances and movements) of the objects. The temporal cognition deals with mid-level abstraction processes which involves temporal or non-spatial encoding (e.g. colour, shape) of the objects, recognition of the patterns (e.g. objects, faces, spoken words).

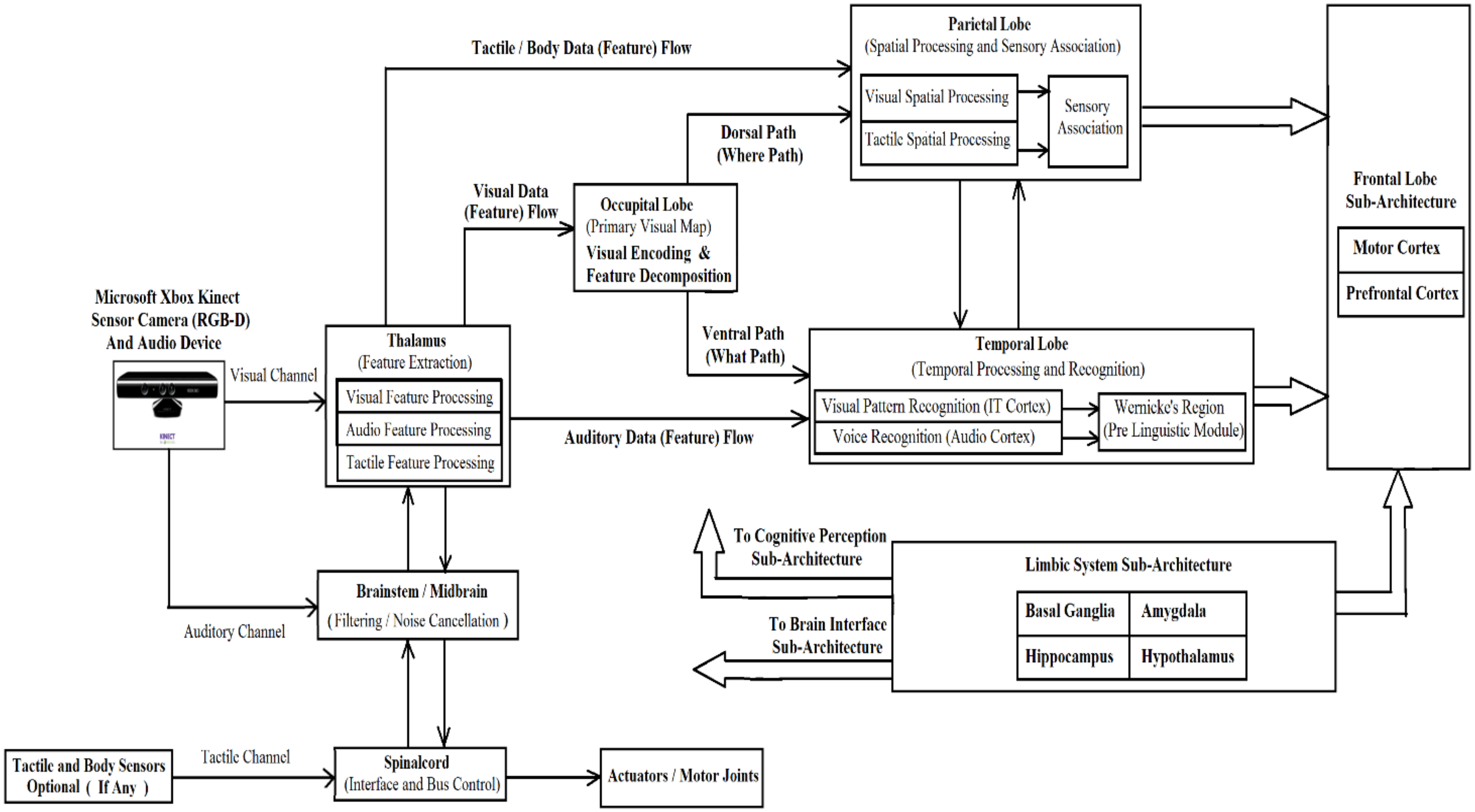


Figure 3.2 : Cognitive Perception Sub-Architecture.

For this framework, various learning paradigms correspond to perceptual cognition. Unsupervised learning methods are utilized for clustering of the feature data in sensory cortex regions while processes related to recognition require supervised learning algorithms to classify patterns.

Our proposed algorithm gives a general outline for the proposed computational architecture. According to order of data flow, the life cycle of generic algorithm proceeds in four main stages. These are pre-processing (thalamus module), early-perception (sensory cortex), processing (cognitive perception) and post-processing respectively.

3.3.1 Thalamacortical Data Propagation for Feature Extraction

In order to propagate the sensory information, thalamus module allows data representation, pre-processing, segmentation, and feature extraction tasks through its computational model. This module captures raw information stream coming from all sensor equipment of the humanoid robot. Audio and visual sensory input data are coming from Microsoft Xbox's Kinect sensor, RGB-D camera including motorized pivot and multichannel microphone array. There are three output channels including visual, auditory and joint position sensors of servo motors that feature data broadcasted from the computational model of thalamus [94].

The computational model of thalamus using RGB-D sensor (Kinect) generates spatial coordinates of human face from segmented RGB and depth images to calculate human's head direction. As visual pre-processing, colour map is obtained by hue saturation value (HSV) conversion. Using the microphone array of Kinect, speech data are acquired from audio stream by a linear prediction filter (LPC) method. Also joint position encoder values of servo motors in the humanoid robot, are transformed to joint angle values via linear scaling [94].

Finally, all frames of process data stream produced in thalamus model are relayed to sensory regions of cortex (e.g. occipital, parietal and temporal). Contextually, pre-processed visual data are transmitted to occipital regions in the computational framework of sensory cortex. The somatosensory data of humanoid robot's body are transmitted to parietal regions.

3.3.2 Sensory Cortex

The broadcasted data (extracted features) coming from thalamus module are processed by different sub-regions in computational sensory cortex model including visual cortex, parietal and temporal lobe. The main responsibilities of sensory cortex including recognition, classification/clustering, sensorial data fusion and interpretation require several different learning activities (e.g. supervised, unsupervised) [46, 96]. Recognition tasks include supervised learning methodologies. Generalization, classification and clustering tasks are usually driven by unsupervised learning procedures. Therefore, unique computational model of sensory cortex is explored to realize design criteria.

3.3.2.1 Visual Cortex

Pre-processed visual data coming from thalamus module are relayed to primary visual cortices in the occipital lobe. Occipital lobe (visual cortex model) is composed of some sub-cortical regions called as primary visual cortices. These visual cortices involved in visual information processing are labelled by V1, V2, V3, V4, PO, MT. Visual data with pre-extracted features coming from thalamus are encoded for transmission to primary visual cortices. The computational model of visual cortex located in occipital lobe generates and initializes several different visual maps. In these regions high order feature extraction tasks are executed.

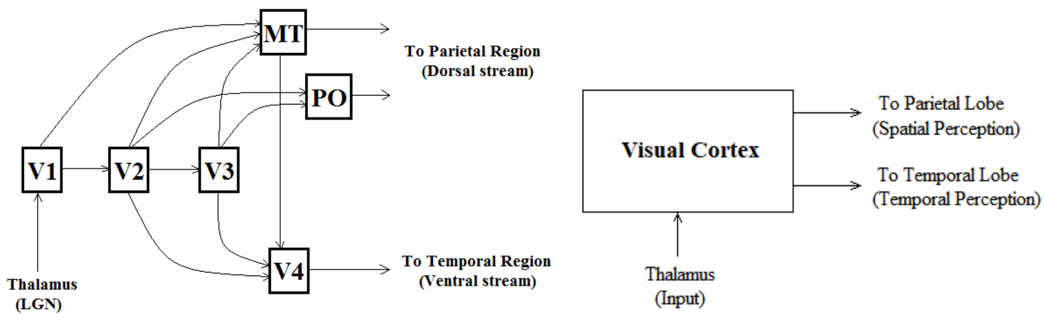


Figure 3.3 : Occipital Lobe in human brain and computational visual cortex.

For example, V1 generates primary visual map. The region V2 applies specific visual masks responsible for visual information relay, which provides detection of region of interests (ROIs). In addition, V3 is sensitive to visual orientation. And main function of region V3 is to project visual information data to V4, PO and MT areas [46]. Some layered structure parts of computational visual cortex are stacked form of several cascaded operations. First of all, a threshold function is applied on colour map image to acquire binary image. Then, the objects in the scene are detected using blob analysis. As a next operation, valid objects are determined in a region of interest.

Using visual perception pipeline (Figure 3.3), deep (detailed) visual features related to object detection in the scene are extracted in visual cortex model. So background isolation from the scene is realized and the number of objects in the scene can be determined. This information extracted from visual perception pipeline are transferred to posterior parts (V4, PO, MT) in computational visual cortex model. Then processed visual data are decomposed into spatio-temporal visual maps. Spatial features of visual data are propagated to parietal cortex. The area PO transmits some physical domain features such as locations (x) of objects. Temporal features of visual data are propagated to temporal cortex by regions V4. The region V4 involves in detection of color and shapes of objects [46]. According to projected 2D coordinates of the objects from 3D locations, RoI of the objects are calculated and binary masks within own RoI's are obtained for recognition (shape detection) of the objects in computational model of temporal lobe. Also, in order to obtain colours of the objects, colour saliency feature maps are generated by colour channels.

3.3.2.2 Computational Model of Parietal Lobe for Spatial Perception

In the human brain, the parietal lobe (or parietal cortex regions) is responsible for spatial perception and sensory data association via incoming data from different perceptual environments (e.g. visual, tactile or somatosensory (body)). For example, coordination between hand and eye can be realized by cortical regions of Parietal lobe [46]. Also body or tactile information (e.g. roughness or smoothness, forces or torques with accelerations, pressure) coming from skin can be processed by somatosensory cortex in the parietal lobe.

In order to realize spatial perception (Figure 3.4) for a humanoid robot, the major task of computational parietal cortex model in the cognitive perception framework is to associate and map perceptual information to movement based behaviours. In this module, processing of spatial domain is carried out including determination of physical measures (e.g., locations, distances, orientations and motions) of objects computed via perceptual data coming from robot's visual features. In addition to this, human's hand pointing or gaze direction are obtained and utilized in learning of the cognitive skills (e.g., motor coordination: object tracking, imitation of human's movements) related to spatial perception.

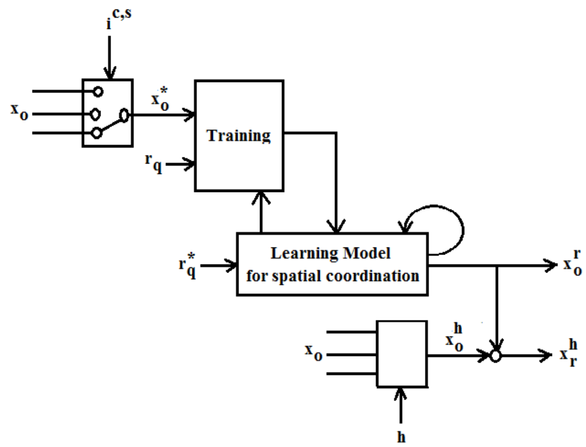


Figure 3.4 : Computational model of the Spatial perception.

Then hand pointing angle (r) with respect to horizontal plane is obtained by forward kinematic model. Head direction angle (h) can be calculated according to head pose estimation using the face positions. x_t^h and x_t^r denote visual locations of the objects from the viewpoints of human and robot respectively. Among the feature vector x^o related to horizontal locations of the objects, target value x_o^* is chosen by the parameters $i^{c,s}$ which are represented as object's indexes of color and shape coming from the computational model of temporal lobe. For spatial cognition, a computational model learns visual locations of the objects from given robot's hand pointing (r) and human's social cue such as hand pointing or gaze direction (h), the spatial relationships between visual saliences and robot's motion space. Learning mechanism of this model is considered as feedforward (MLP) neural network which has 1 hidden layer with 10 neurons. It executes simple regression task related to object pointing and tracking task. For comparison purpose, several methods such as SVM, decision tree, nonlinear regression are utilized.

3.3.2.3 Computational Model of Temporal Lobe for Non-Spatial Perception

The computational model of temporal region is a part of the brain inspired cognitive perception framework. This model is responsible for non-spatial and temporal perception. It includes the models related to visual and auditory perception.

Visual memory and pattern recognition processes are realized by cortical regions (TEO/TE) located in visual perception part of brain's temporal lobe [46].

Computational model of this cortical regions employing two learning mechanisms is sensitive to colour and shape features of visual information coming from V4 region of occipital lobe via ventral data stream. This visual data stream is seeded into visual regions (TEO/TE) of temporal lobe. For learning mechanisms of this model, firstly, they are considered as feedforward (MLP) neural network which has 1 hidden layer with 10 neurons. $W_{c,s}$ are weight matrices and $b_{c,s}$are bias vectors. The input vector x^c includes $[r, g, b]$ values for color recognition, and x^s contains $[\Delta x, \Delta y, \Delta x/\Delta y]$values for shape recognition.Δx represents the width of the object. Δy depicts the height of the object. $\Delta x/\Delta y$ provides the aspect ratio height-width.

$$y_{TE}^{c,s} = f(\, W_{c,s}x^{c,s} \; + \; b_{c,s}) \tag{3.1}$$

Upper indices (c,s) of the $x^{c,s}$ vectors represent colour and shape feature data respectively (Figure 3.5). Feature vectors $x^{c,s}$ related to shape and color of the objects are chosen by the parameter i^r (Figure 3.5), which is coming from the computational model of parietal lobe. This neural network is trained by stochastic gradient descent (SGD) with momentum. So classification (shape, colour) of the objects is realized for the recognition task. In addition, several methods such as SVM, decision tree, kNN, naïve Bayes and CNN are utilized for comparison purpose.

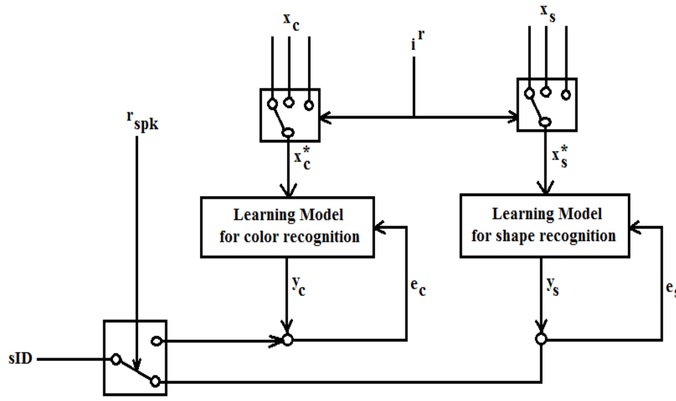


Figure 3.5 : Computational model of the temporal lobe.

Temporal lobe is one of the major regions for auditory processing. The computational model of auditory cortex in this region is involved in speech recognition. For speech recognition, according to audio feature information (LPC vectors) coming from thalamus, tokenized spoken words are recognized by hidden markov models [97]. In the test stage, output of the system are returned as tokenized words (labels) with their recognition probability. The parameter y_{sp} is used as the target data for training of the proposed neural networks.

$$y_{sp} = speechnet(f); \tag{3.2}$$

In the interaction experiments, events recorded as binary true or false responses are represented by a sequence as the variable *TF* in a temporal memory fragment.

if ($y_{TE}^{c,s} == y_{sp}$)
    $TF_t = 1;$
else
    $TF_t = 0;$
end

3.3.3 Attention Modelling

Establishing joint (or shared) attention between human and robot is based on two domains. One of the domains is the attention model related to human side. The other domain is the attention model related to robot side. These attention models measure their own focuses (e.g. human's or Robot's focuses). The human's and the robot's focused attention models are associated by selective attention model in the computational cognitive perception framework of the humanoid robot. According to a social signal as selective cue, perceived by human's attention model, the robot's attention model focuses on an object or an event with priority of the selected focus.

$$x_r^h = x_o^r - x_o^h \tag{3.3}$$

x_r^h and x_o^r denote visual locations of the objects from the viewpoints of human and robot respectively. So the tracking error (the pointing error) are observed as x_r^h since spatial perceptual model learns visual locations of the objects from given robot's hand pointing *(r)* and human's social cue such as hand pointing or gaze direction *(h)*.

$$p_{c,s}^t = \frac{\sum_{i=t}^{t+\Delta t} TF_i}{\Delta t} \tag{3.4}$$

For a defined time window (Δt), performance values p_c^t, p_s^t of the event sequence related to temporal perception are computed according to demonstation and observer phases respectively.

3.4 Implementation

Some implementation procedures related to the proposed solution are considered. The problem description requires an experimental setup for implementing an interaction scenario between human, robot platform and environment.

3.4.1 The Experiments

In conducted experiments, the experiment scene consists of several objects which are located on a platform (e.g. small table) as shown in figure 3.6. In the spatial workspace of robot (Figure 3.7), the objects have different features (e.g. size, shape, colour, material, location, etc.). In addition to them, humanoid robot and human are presented as face-to-face. Also, the small table, which includes the objects, resides between human and the robot.

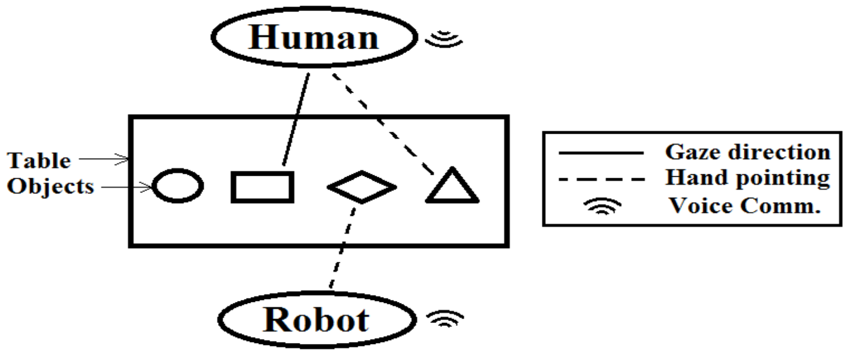


Figure 3.6 : Experimental setup.

Humanoid robot platform accepts audio, visual and a set of its joint information. Audio input is appraised as speech commands. Visual inputs are regarded as gaze direction and skeletal information of human for hand pointing. Also another visual source is reserved for saliences (e.g. ID, colour, location) for object or gesture recognition. The internal inputs related to robot's body are joint angles, gyro and proximity information.

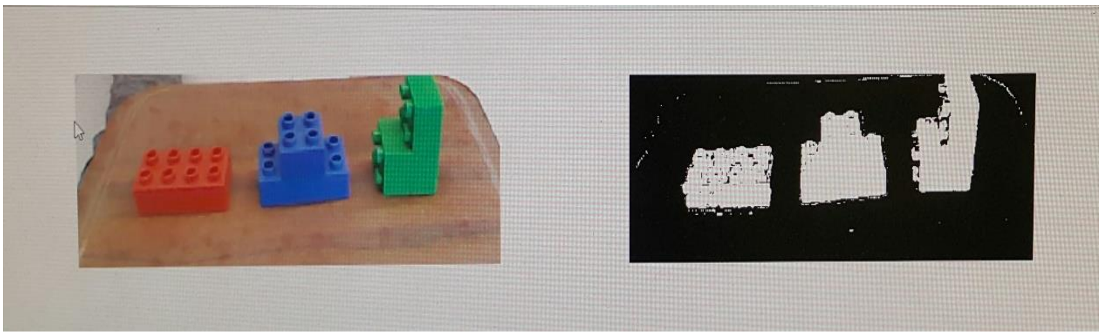


Figure 3.7 : Objects and their binary masks.

Humanoid robot platform can execute some gestural behaviours like hand pointing as output actions (or motor commands). Due to physical constraints, gaze behaviour of the robot is only performed by tilt angle movement of robot’s head (pivot motor in Kinect sensor). In addition to that, the robot can give speech commands. According to purposes of the study, flow of the main experiment scenario can be described as follows:

A humanoid robot and a human participant play an interaction task. In the training session, the humanoid robot shows an object in the experiment table by hand pointing. Meanwhile it requests that the human instructor says the colour and the shape of the object. So the saliences to be focused are learned by the humanoid robot. As a test session, the human subject asks the colour of an object pointed by hand or gaze direction of him. It is expected that the humanoid robot is forced to focus on the object and say its colour according to human’s social cue.

3.4.2 The Scenario

In test scenario (Figure 3.8) of this study, humanoid robot executes a sequence of behaviours generated by its computational neurocognitive architecture. This system is able to classify, recognize and model the objects according to their special characteristic features. Spatial perception is performed for environmental (workspace) awareness of the robot while temporal perception is employed to identify the objects in the robot’s workspace. To emerge perceptual cognition, some turn-taking (sequential) interaction tasks and focusing practices on the objects are performed (Figure 3.7).

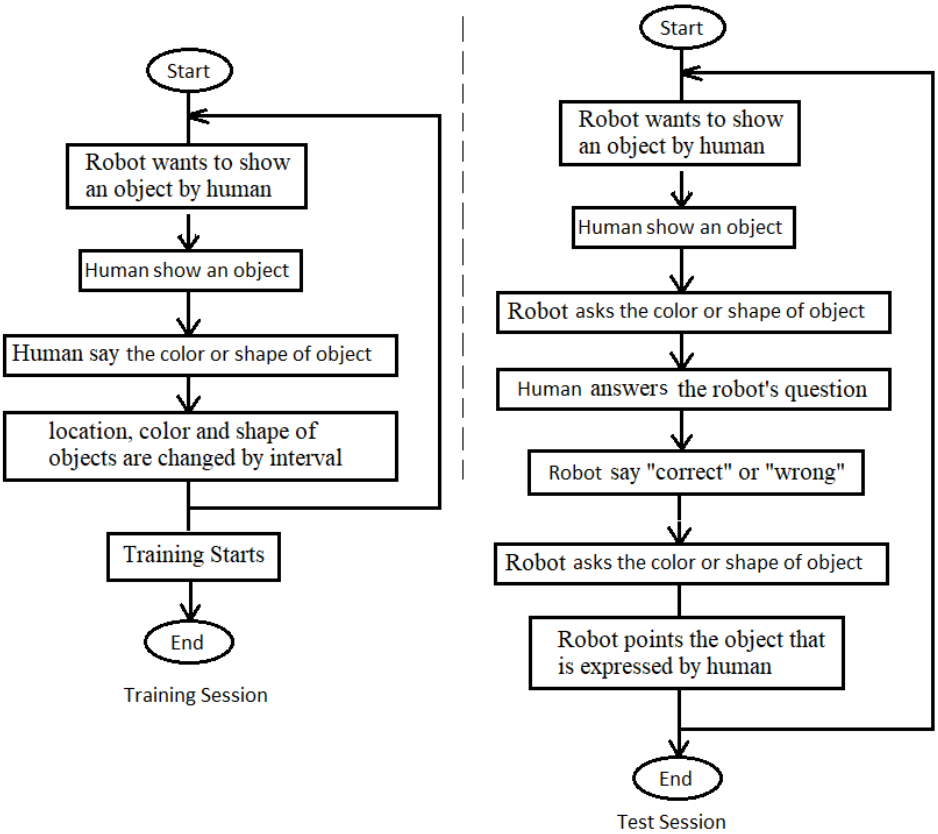


Figure 3.8 : Scenario flow.

The humanoid robot stores the interaction history. The interaction history is recorded into a database. At the end of the experiments, the interaction data are analysed. Performance of cognitive perception and contribution of the neuro-cognitive architecture embodied in the humanoid robot are eleboratively discussed.

3.5 Experimental Results and Performance Evaluation Results

The computational perceptual system framework for a humanoid robot is modelled, simulated, and tested in a Matlab programming environment. There is a software development kit (SDK) for bioloid robot platform. For communication between hardware of humanoid robot and SDK, firmware of bioloid robot platform was updated before the experiments.

In the proposed experiment scene (Figure 3.9), three objects are scattered in the workspace of the robot. The objects including Lego blocks are perceived by cognitive perception system according to their features (e.g. shape, colour). During the experiment, the robot collects these features and constructs datasets.

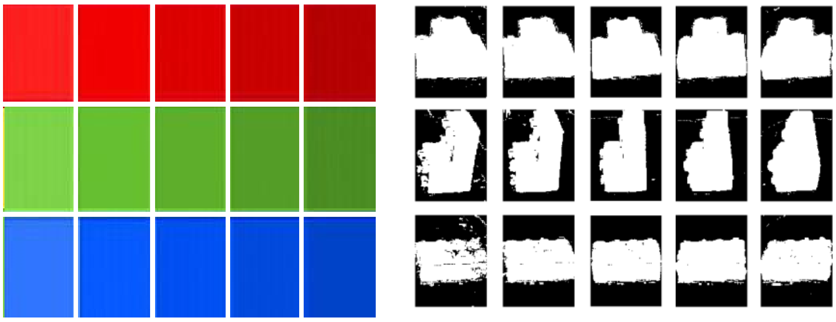


Figure 3.9 : a) Color dataset, b) Binary masks for shape detection.

At the first stage, data capturing and preparation processes are performed for all types of stimuli by thalamus. Then primary visual cortex realizes additional feature extraction tasks. These tasks are acquiring colour map and detecting blobs from the binary images. The colour map derived from rgb images provides a domain for colour extraction of the objects. It uses hue, saturation, and value (HSV) instead of red, green and blue (RGB) format. As preprocessing tasks, segmented images as binary masks shown in figure 3.8.b help to obtain region of interests (ROIs). Also some standard procedures like normalization, thresholding and gray level images converted from RGB are performed in this region.

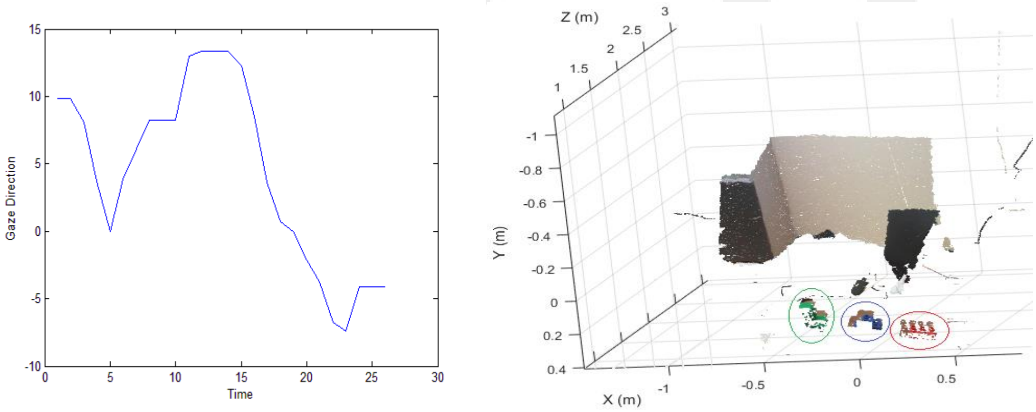
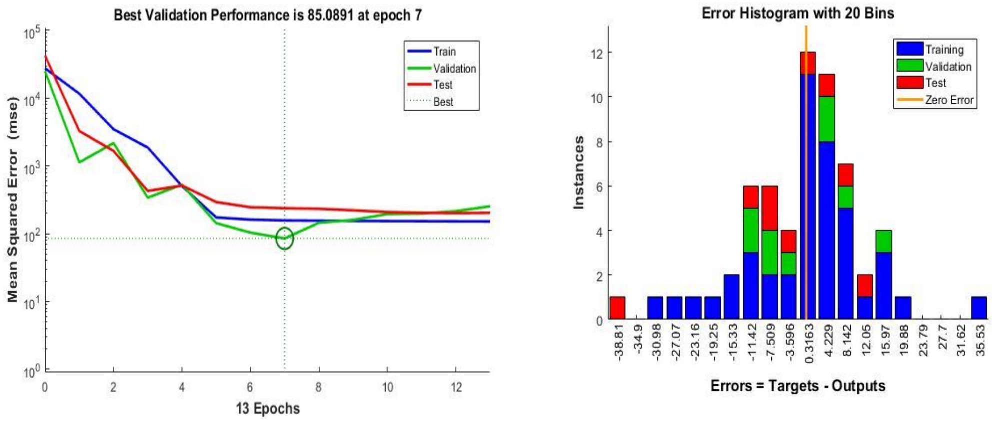


Figure 3.10 : a) Gaze direction, b) Point cloud of the objects.

The visual information from the viewpoint of the robot, is shown in figure 3.10. Robots vision system including Kinect sensor as a RGB-D camera provides both RGB and depth images. By infrared scanning of depth sensor, depth images are made of spatial point cloud (set) in the 3D meshed lattice as a work space of the robot.



(a) (b)

Figure 3.11 : a) Validation performance, b) Error histogram.

Training performance and error histogram of neural network for object pointing (or tracking) task related to spatial perception are presented in figure 3.11. For this task, 122 samples are used, where 85 of them are the chosen for the training dataset. From the rest of 37 samples, 19 samples are used as validation and 18 samples are used as test datasets. According to scaled error histogram in figure 3.11.b, training, validating and test errors which are depicted as blue, green and red bars are 0,0157, 0,0167 and 0,042 respectively. I In addition, convergence occurred in approximately 7th epoch for training, validation and testing.

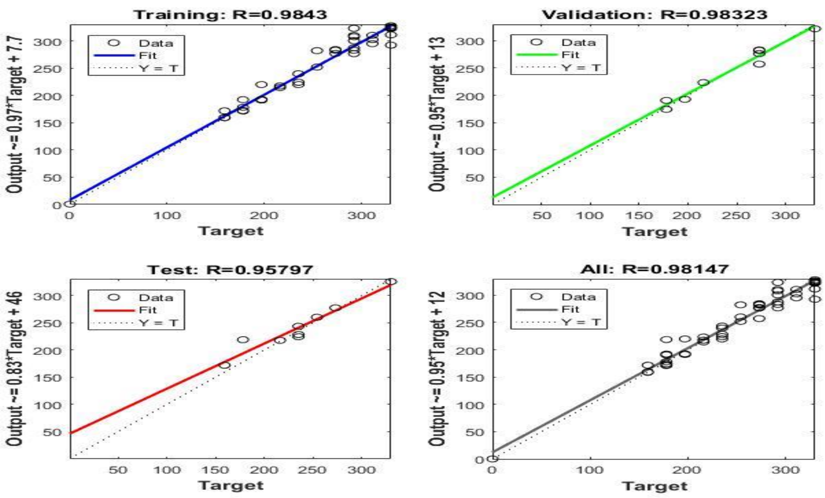
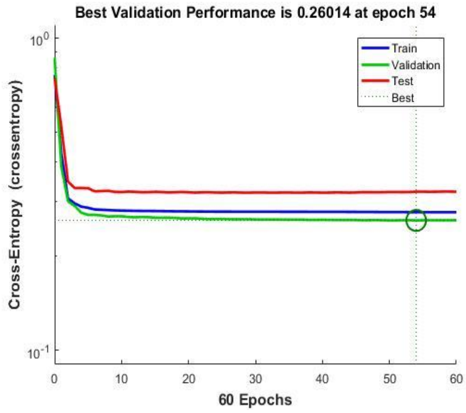
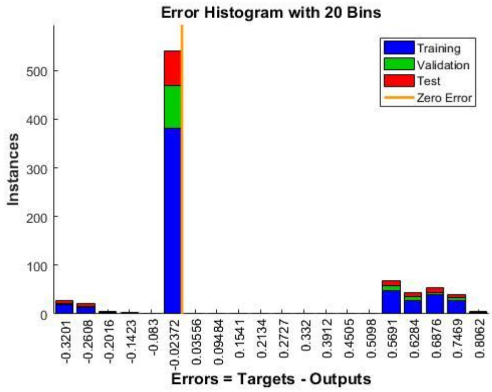


Figure 3.12 : Regression outputs.

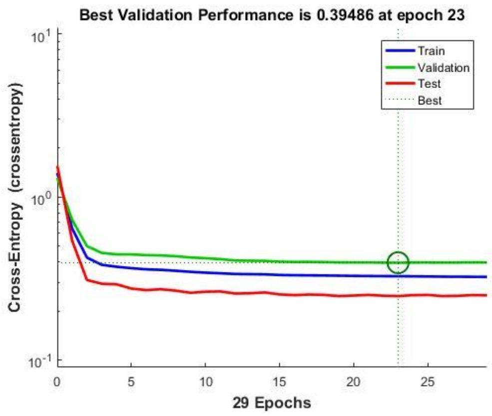
Regression results related to neural network model using mean square error function are shown in figure 3.12. According to these results, with small tracking error, the robot can track the pointed objects and learn the points of the objects where are located in. Momentum update parameter is 0,001 and minimum gradient performance parameter is 0,0000001. In addition, the results related to SVM, nonlinear regression and decision tree models are presented in table 3.2 for comparison purpose.



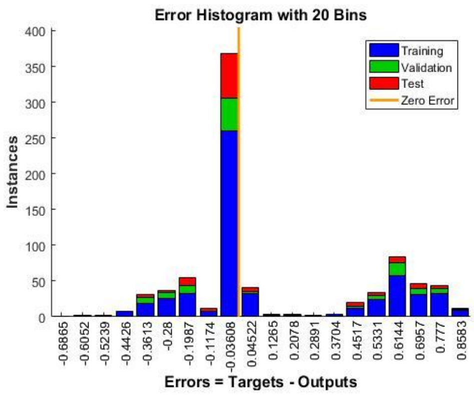
(a)



(b)



(c)



(d)

Figure 3.13 : Training performances of color and shape recognition.

Neural network training performance and error histogram of color and shape recognition task related to temporal perception are presented in figure 3.13. For color recognition, training, validating and test errors which are represented as blue, green and red bars are 0,023, 0,056 and 0,001 respectively. For shape recognition, training, validating and test errors are 0,036, 0,001 and 0,056 respectively. Cross entropy performance function is preferred in both model. Minimum gradient is 1e-6. Sigma determining change in weight for second derivative approximation is 5e-5 and lambda which is a parameter for regulating the indefiniteness of the Hessian is 5e-7. Convergence related to training of the colour recognition occurred in 54th epoch and convergence related to training of the shape recognition occurred in 24th epoch.

During the experiment, while feature vectors are collected, responses of a human subject are stored as target vectors. For this task, 122 samples are used and 86 of them are the training dataset. From the rest of 36 samples, 18 samples are used for validation and 18 samples are used for test datasets. Then these constructed datasets are used for training for colour and shape recognition of the objects. In the test case, robot recognizes colour and shape of an object according to given human's social cue.

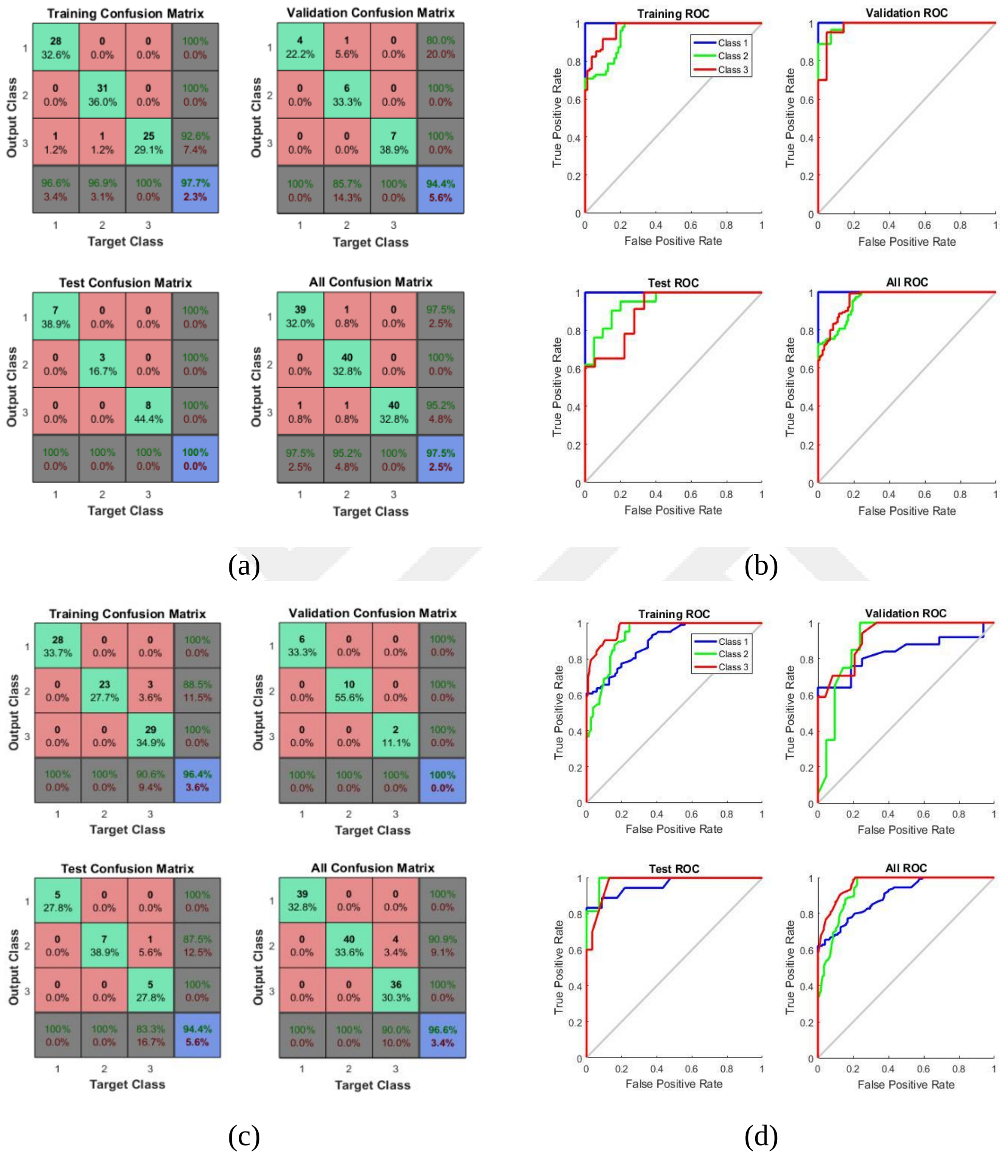
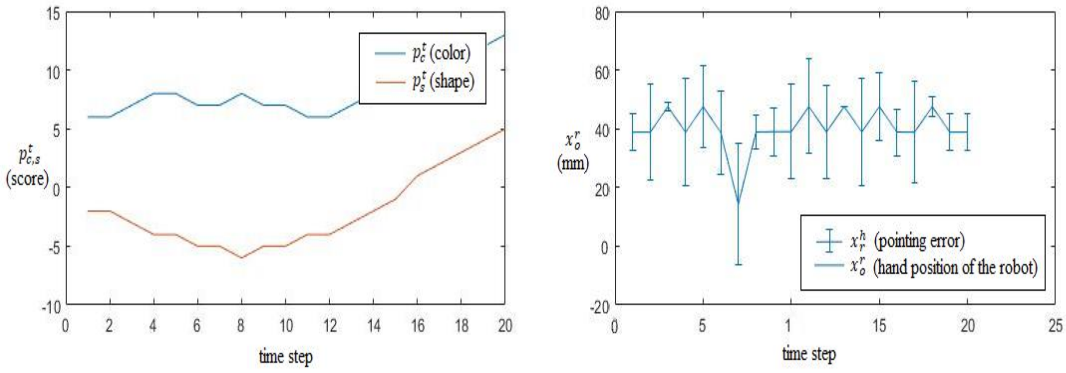


Figure 3.14 : a) Color detection results, b) Shape detection results.

Recognition results of neural network are presented by confusion matrices and receiver operating characteristic (ROC) plot in figure 3.14. The results related to figure 3.11-14 show the efficiency associated with research question 1 (RQ1). In addition, the results related to SVM, kNN, naïve Bayes, CNN and decision tree models are presented in table 3.1 for comparison purpose.



(a) (b)

Figure 3.15 : Learning statistics of the recognition processes.

The performance of the recognition process which are associated with research question 2 (RQ2) are presented in figure 3.15.a. Figure indicates the performance of the recognition process. Spatial perception performance is observed in figure 3.15.b. According to given selective stimuli, objects in workspace of the robot are recognized by temporal lobe of the cognitive perception system. In addition, recognized objects as a focus are labelled. Temporal focus includes attributions like colour and shape of the object.

Table 3.1 : Comparison of the classification models.

Model No.	Classification Models	Colour recognition	Shape recognition
1	SVM	%94	%93
2	KNN	%92	%95
3	Decision Tree	%92	%95
4	Naive Bayes	%95	%94
5	MLP	%97	%96
6	CNN	%99	%98

In table 3.1, different classification models were compared for colour and shape recognition. It can be observed that although all results were close each other, convolutional neural network gave the best result.

Table 3.2 : Comparison of the regression models.

Model No.	Regression Models	Pointing or Tracking Task
1	SVM	%94
2	Decision Tree	%92
3	Nonlinear regression	%95
4	MLP	%98

Several regression models were compared for pointing or tracking task (Table 3.2). According to results, the best result was achieved via feedforward neural network (MLP). In addition, errors related to speech recognition and object pointing task of the human subject were obtained as %12 and %14 respectively.

4. COMPUTATIONAL LIMBIC SYSTEM SUB-ARCHITECTURE

4.1 Motivation

From a reverse-engineering perspective, it is essential to construct a suitable computational intelligence infrastructure for a humanoid robot [94]. The proposed framework (Figure 4.1), inspired by the limbic system in the human brain, is a computational cognitive architecture including the hippocampus, basal ganglia, hypothalamus, and amygdala [6]. It allows regulation and monitoring of behaviour and cognitive processes in humanoid robots, realizing a variety of cognitive functions: generation of emotional expression, behaviour switching, motivation, and long-term memory (LTM) [6]. This section deals with the research questions (RQ3 and RQ4) and evaluates the hypotheses (H1 and H2) depicted in the section 1.4.

4.2 Computational Framework of Limbic System

In this study, there are three main contributions to the literature. The first one is that the computational approximation of the cortical regions in the human brain is developed in a software framework [94]. Cognitive functions, which process emotional responses, form episodic memory, and select the appropriate behavioural action sequences are separately modelled for each component (region) of it. Secondly, in order to realize these functions, we propose a novel approach, employing a computational neural tissue, which has multiple dynamics. The dynamics used in this structure include spiking neurons, neural mass (e.g. neural population) and dynamic neural field. This is achieved by combining them with soft computing techniques in accordance with different requirements of the limbic system modules (e.g. basal-ganglia, amygdala, hypothalamus and hippocampus). Finally, utilizing the reinforcement learning-based adaptation (plasticity) procedure, the synaptic strengths (weights) of episodic memory in the hippocampus are updated through the emotional reward activation, in the amygdala, and the working memory, in the prefrontal cortex, during the action selection processes in the basal ganglia [94].

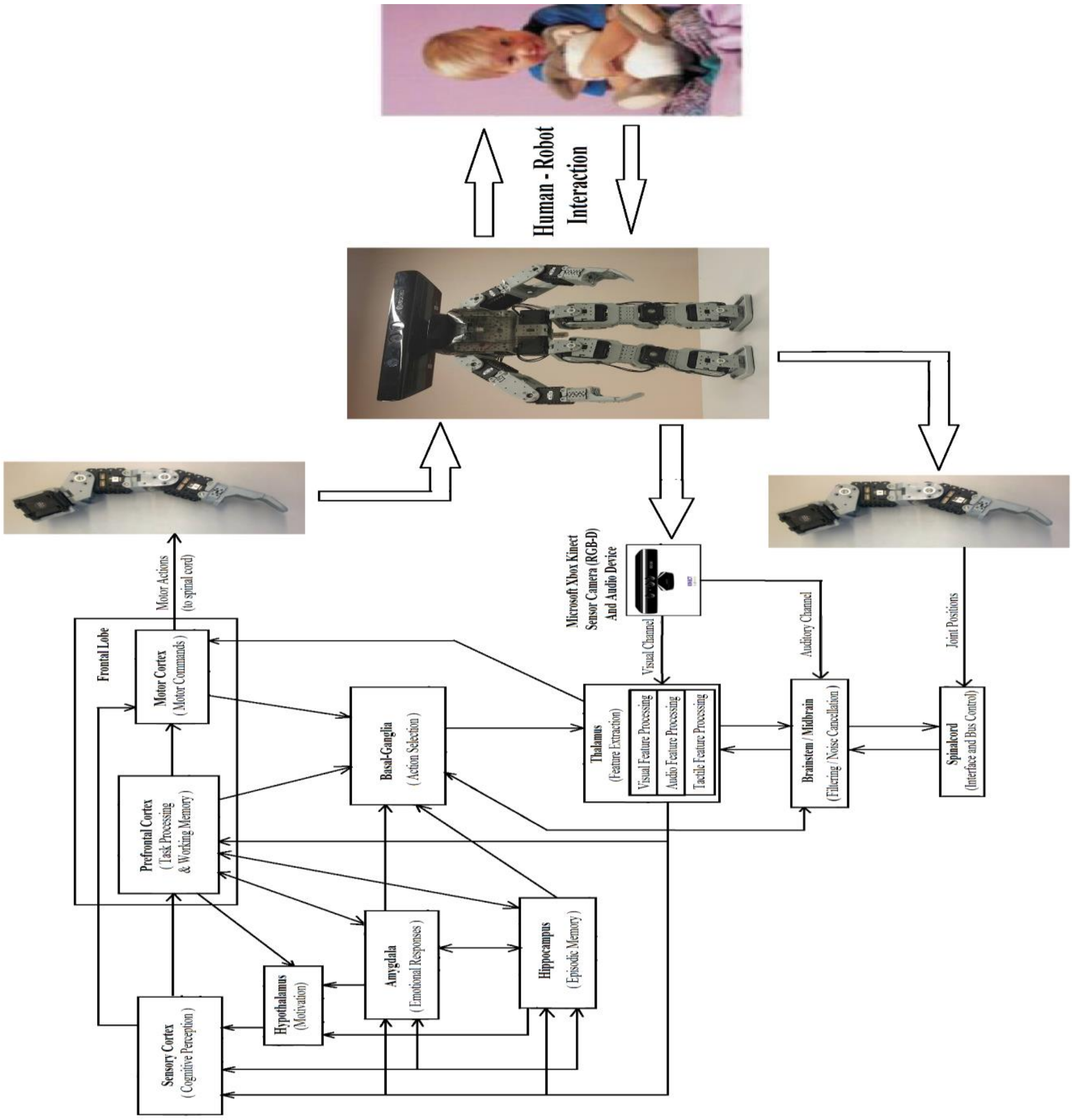


Figure 4.1 : Brain-inspired neuro-cognitive arctitecture (Limbic System) [94].

In order to improve a child's attention, a humanoid robot's emotional activity giving rewards for optimal action selection allows to boost the attention level of preschool child with ADHD via an action selection mechanism [46]. Also, reinforcement learning methods train and update the weights of procedural memory, a kind of memory related to action selection (or execution) skills, through emotional reward activations allowing the adaptation policy of the framework to be realized. Therefore, the presently proposed computational limbic system framework may provide a novel solution to ADHD issues including low level focusing, learning difficulties [94].

4.2.1 Cognitive Perception

In this section, cognitive perception system is described since it constructs the perceptual model of the robot interacting with humans [6]. This part of the architecture related to cognitive perception is composed of two major cortical regions namely thalamus and sensory cortex [94]. Also, these cognitive modules have their own specialized perceptual functionalities. Before cognitive perception processes, some feature extraction tasks realizing segmentation, edge detection and filtering are performed as data pre-processing activities [6].

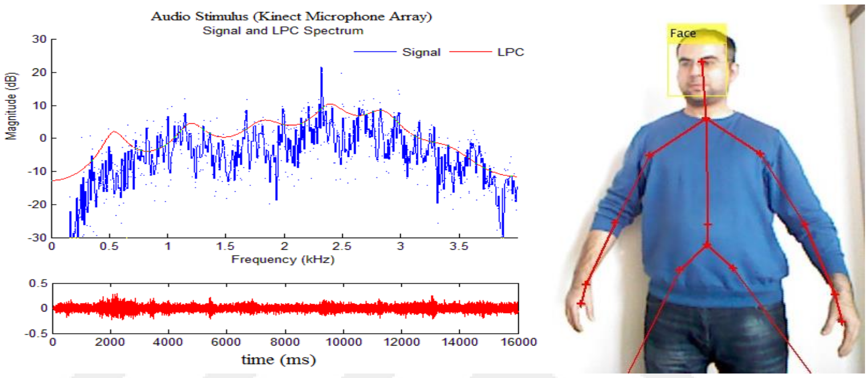


Figure 4.2 : Acqusition of the sensory stimuli (Auditory and Visual).

Sensory information is acquired through all sensors of the humanoid robot. The robot's sensory (input) resources are adapted to record vision, auditory, and somatosensory information (e.g., body sensors like gyro, joint position encoders, IR, etc.). Audio and visual sensory input data (Figure 4.2) come from Microsoft Xbox's Kinect sensor, an RGB-D camera with motorized pivot, and a multichannel microphone array. These hardware specifications and experimental setup are explained in further subsections. There are three output channels (visual, auditory and somatosensory) that feature data are broadcasted from the computational model of thalamus [94].

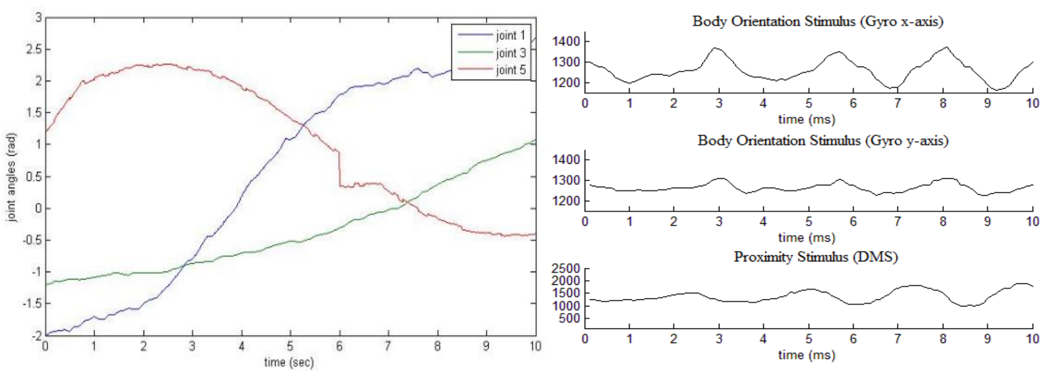


Figure 4.3 : Acqusition of the sensory stimuliin the robot's perception environment.

In order to propagate the sensory information, the thalamus module allows data representation, pre-processing, segmentation, and feature extraction tasks through its computational model (Figure 4.4). This module accepts a raw sensory information stream [6]. Some data preprocessing tasks have been applied on this raw data stream; such as noise cancellation, normalization, and dimension reduction. The computational model of thalamus using an RGB-D sensor (Kinect) generates spatial joint coordinates of human skeletal structure from segmented RGB and depth images, and the coordinates are projected onto a two dimensional plane. Then it performs coordinate/angle conversion. Also visual pre-processing is performed by multiscale linear filtering so that brightness, colours, shapes and distances of objects can be extracted for visual processing. Using the microphone array of Kinect, speech data can be acquired from audio stream by a method like linear prediction filter (LPC) or Fourier transform. The other sensory feature extraction tasks related to the body of humanoid robot, can be performed by utilizing body sensory equipments. Finally, all frames of process data stream produced in thalamus model are relayed to sensory regions of cortex[94].

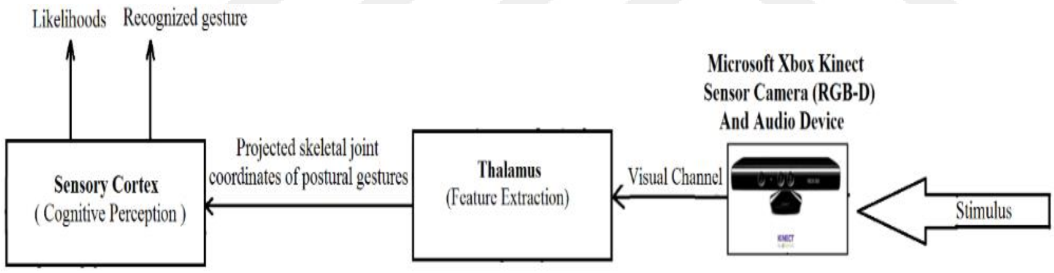


Figure 4.4 : Feature Extraction and Cognitive Perception Pipeline.

After this stage, the cognitive perception module evaluates likelihoods of postural gestures using projected skeletal coordinates. A possible gesture having the maximum of the likelihoods is selected as a recognized gesture [94]. Cognitive perception functions perform several tasks including feature extraction and pattern recognition. These properties play an important role in modelling of the perceptual attention.

4.2.2 Amygdala for Emotion Modeling

The computational model of the amygdala module (Figure 4.5) plays a major role in the processing of emotional memory and responses of the emotions [6, 94]. It is composed of several sub-nuclei, which employ accessory basal nucleus (AB), lateral nucleus (LN), basal nucleus (BN), and central nucleus (CN) [46, 98]. Output terms are forwarded to the hippocampal regions, the basal ganglia, the hypothalamus, the brainstem components (midbrain, medulla, VTA etc.), and the associative regions (prefrontal/orbitofrontal cortices). Input terms are directed toward the sensory cortices, the thalamus, the entorhinal cortex of the hippocampus, and the frontal lobe areas (e.g., prefrontal/orbitofrontal cortex).

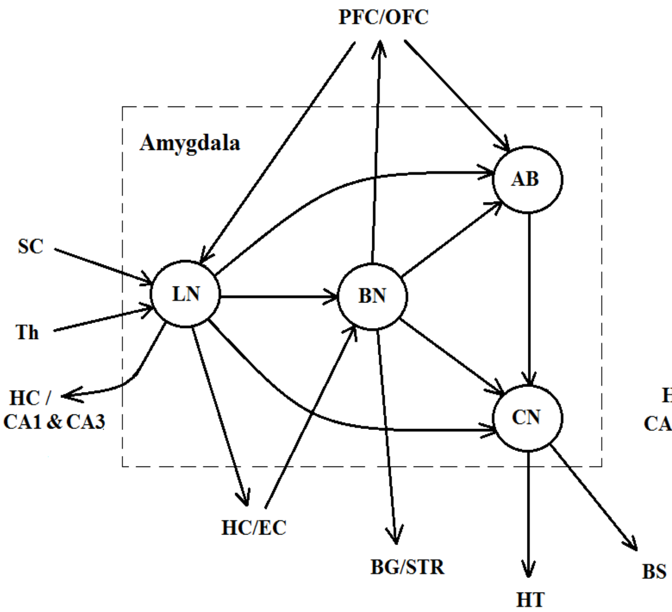


Figure 4.5 : Architectural formulation of Amygdala module.

Particularly, the amygdala operates as a reward generator providing emotional responses to the other cerebral and cortical regions [98].

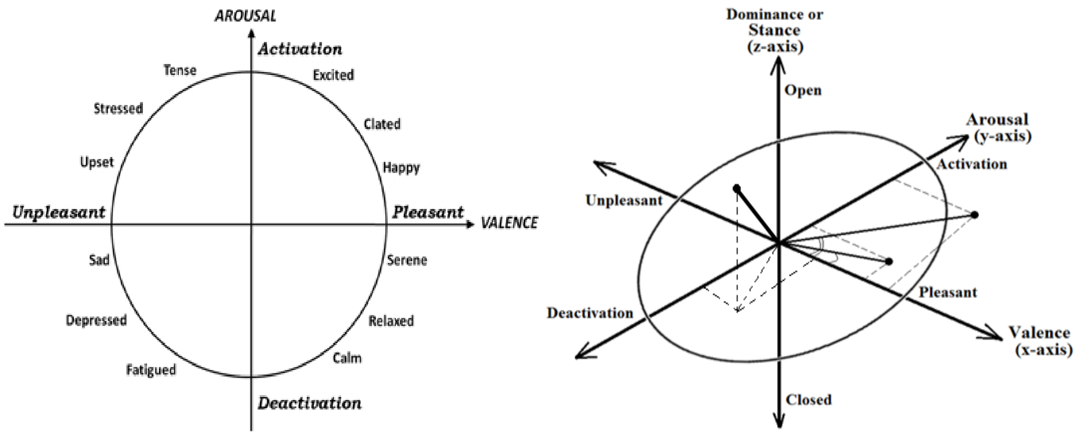


Figure 4.6 : Representation of emotions in 2D and 3D domain [99, 100].

Mathematically, artificial emotions can be expressed in the analytical domain as shown in figure 4.6. The progress of appraisal or emotional feature extraction generates a tuple (arousal (A), valance (V)) computed by equations (4.1) and (4.2) [99]. Value likelihood related to recognized gesture stems from the perception stage and t_{resp} is the response time of the recognized gesture.

$$A = 2.tanh(1/t_{resp}) - 1 \tag{4.1}$$

$$V = 2.tanh(10/likelihood_{resp}) - 1 \tag{4.2}$$

Extracted data can be formulated in stimulus activation $I_{Am}(x,t)$, which is of a two dimensional Gaussian form, where$x = (A,V) \in \mathbb{R}^2$. Emotional responses and expressions released by the dynamic neural field $U_{Am}(x,t)$ of the amygdala (Figure 4.7), using this reinforcement influence [79] on the association between sensory and motor systems, are composed of long-term memory stored in the weights.

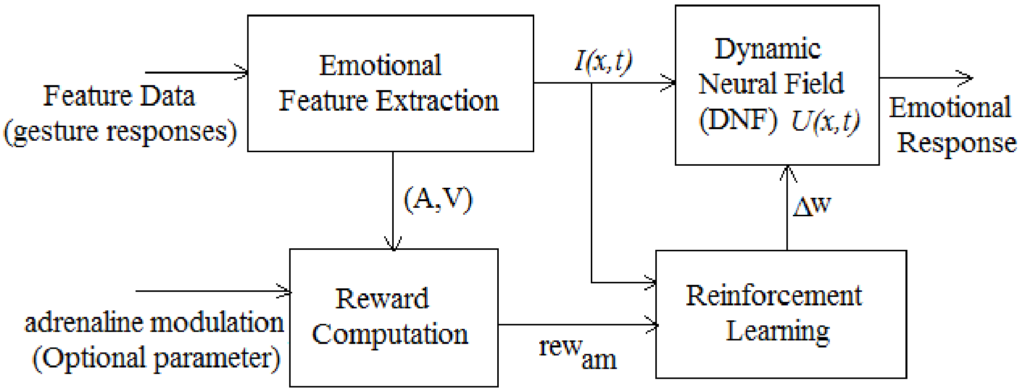


Figure 4.7 : Computational model of amygdala for emotional response generation.

$$rew_{am} = \frac{ad}{\sqrt{(1-A)^2 + (1-V)^2}} \tag{4.3}$$

The reinforcement reward can be computed by equation (4.3). Additionally, the term *ad* is an optional parameter to allow adrenaline modulation to fine tune the reinforcement learning progress. Emotional memory is stored in the weight matrix in the computational model of the amygdala [6]. In this memory, emotional activation may be increased or diminished according to learning progress.

4.2.3 Hippocampus

The hippocampus module is the major component of the emotion-imitating and brain-inspired cognitive architecture [94]. It is composed of several computational sub-nuclei models, including entorhinal cortex (EC), dentate gyrus (DG), subiculum (Sub), CA1, and CA3 [46, 98, 101]. The nonlinear dynamic nature of the hippocampus includes stochastic and chaotic behaviours, such as dynamic strange attractors. Long-term declarative and associative memory formation stored in the synaptic weights of hippocampus is operated through convergence to some specific equilibrium points or limit cycles [6, 94].

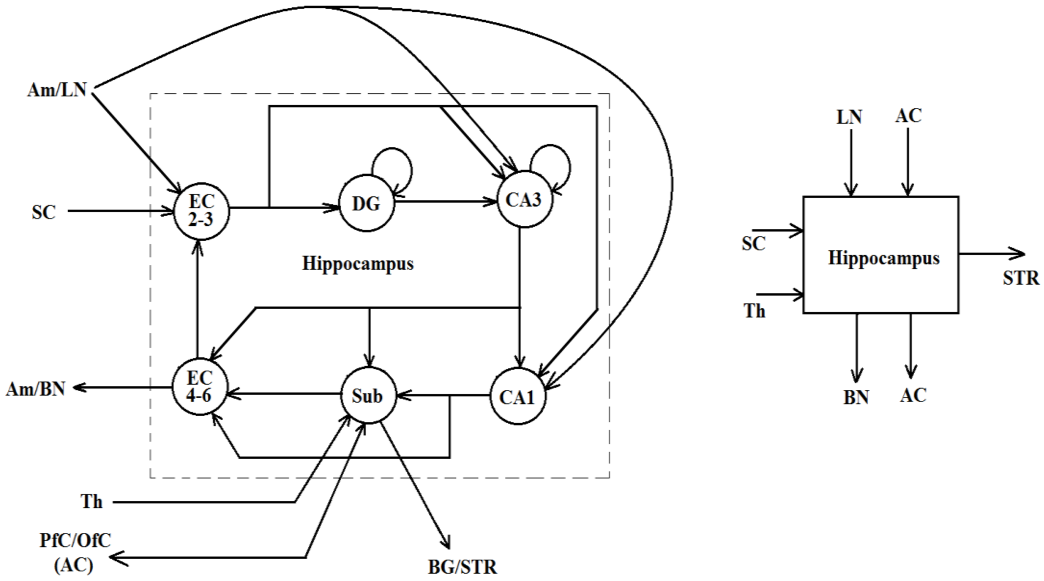


Figure 4.8 : Neural circuit structure of Hippocampus.

Every node contains its own neural population, which has different characteristics and information processing procedure (Figure 4.8). The training session is mostly proceeded in DG, whereas recalling activities are realized in CA3/CA1. The EC regions are responsible for interaction with other regions, like the neocortex and the parahippocampal region [46, 101].

The hippocampus also contributes to other cognitive skills, such as spatial navigation, self-awareness, and consciousness, by assisting other critical cerebral and cortical regions, like the frontal lobe (e.g., prefrontal/orbitofrontal cortex) and the sensory-motor areas[98, 101]. The computational nature of the hippocampus does not only enable episodic memory function, which is a type of declerative long-term (LTM) memory, but also semantic memory, which assigns meaning (description) to objects or events. The internal dynamics of the hippocampus represent firing rate activities of subneural populations having EEG like signal density [46].

A fragment of the memory in the hippocampus is composed of several cognitive activities. As declarative memory, episodic memory formation, which can store past events (e.g. interaction history), involves measurement or detection of the attention level of a human during interaction. Influences of the working memory (WM) in the prefrontal cortex affect the hippocampal activities primarily [46]. The working memory, as a short-term memory, describes a workspace storing short-term past, current, and future (predictive) events or navigational spaces. The computational equivalent of the hippocampus is responsible for establishing bridges between the working memory (short-term) and the formation of episodic memory (declarative and long-term). Furthermore, emotional state transactions involving feelings in the Brodmann area (BA10) of the prefrontal cortex and emotional responses of the amygdala pass to the hippocampal memory, so that moods can be modelled and observed in the longer-term emotional state [5]. Figure 4.9 explains effectiveness of the different emotional processing levels and their activation times.

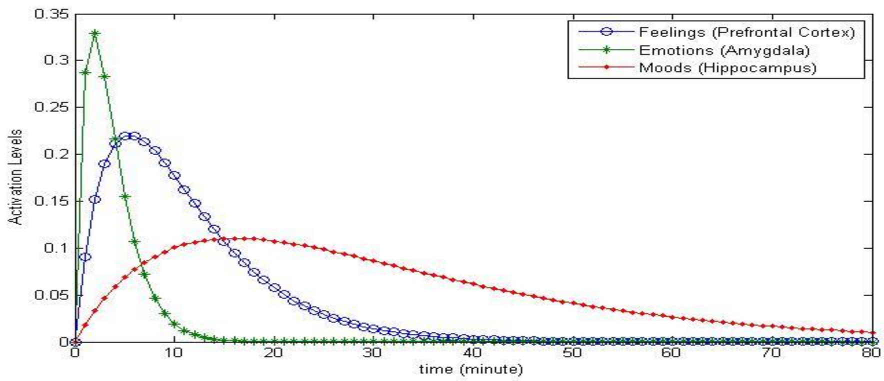


Figure 4.9 : Long-Term Potentiation (LTP) over emotional processing.

Output terms are expressed as striatum of the basal ganglia, the frontal lobe areas (e.g., prefrontal/orbitofrontal cortex) and the basal nucleus in the amygdala. Input terms are directed to the sensory cortices, thalamus, lateral nucleus of the amygdala, frontal lobe areas (e.g., prefrontal/orbitofrontal cortex) [46].

Working memory (WM) is represented by the sequence of events within a given time window (Δt) as a fragment of the memory. Events recorded as binary true or false responses are stored in the variable TF in the interaction; thus enabling the computation of interaction performance scores $p(t)$ for the defined short-time span, and feeding episodic memory[94]. A fragment of the memory in the hippocampus is composed of several types of information including perceptual observations (e.g. recognized gestures), assigned tasks, emotional states and executed actions[94].

$$p(t) = \frac{\sum_{i=t}^{t+\Delta t} TF_i}{\Delta t} \quad (4.4)$$

$$I_{HC}(x,t) = A.\exp(-\frac{(x-p(t))^2}{2.V^2}) \tag{4.5}$$

Hippocampal stimulus is formed along its feature space (x) as a Gaussian function whose amplitude and variance are arousal (A) and valence (V) values of emotional states, respectively. The memory field in the computational hippocampus module can be formulated in its dynamic neural field $U_{Hc}(x,t)$. This neural field $U_{Hc}(x,t) = \{ U_{Hc}(x,t_0 \to t_{stm}),\ U_{Hc}(x,t_{stm} \to t_{ltm}) \}$ can be divided into two time periods of memory: short- and long-term memory. Short-term memory (STM) is expressed as neural field $U_{stm}(x,t)$ with its own time period $t: t_0 \to t_{stm}$. Similarily, the long-term memory (LTM) storing past interaction data (e.g. field activations related to realized events) is considered as neural field $U_{ltm}(x,t)$ with a larger time period $t: t_{stm} \to t_{ltm}$. Time indices t_0, t_{stm} and t_{ltm}indicate initial, short-term and long-term times respectively[94].

$$U_{stm}(x,t) = U_{Hc}(x,t_0 \to t_{stm}) \tag{4.6}$$

$$U_{ltm}(x,t) = U_{Hc}(x,t_{stm} \to t_{ltm}) \tag{4.7}$$

The unsupervised learning procedure in the proposed computational hippocampus model is applied to the short-term memory field $U_{stm}(x,t)$ which is a part of the hippocampal neural field $U_{Hc}(x,t)$. The self-organizing map (SOM) algorithm [80], as a type of unsupervised learning procedure, provides clustering of the map (neural field $U_{stm}(x,t)$), after which the learned memory pattern is passed into the neural field $U_{ltm}(x,t)$ of long-term memory (Figure 4.10).

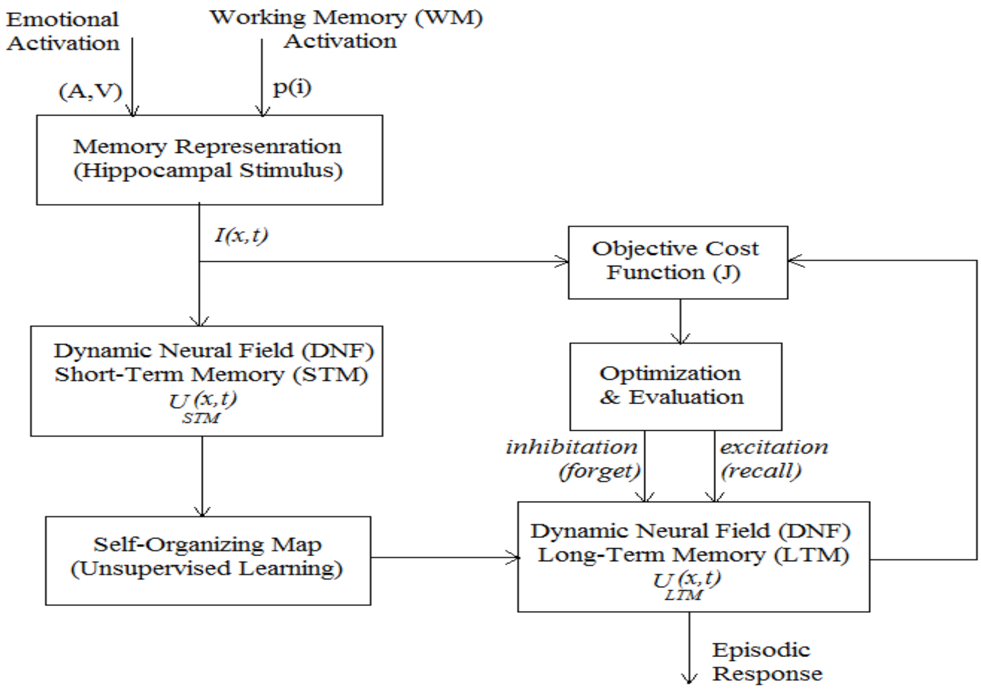


Figure 4.10 : Computational model of hippocampus for episodic memory.

Recalling and forgetting functions corresponding to neural activities of excitation and inhibition, respectively, are realized in the LTM neural field $U_{ltm}(x,t)$. The proposed cost function is given by:

$$J(x) = \|I_{HC}(x,t) - U_{ltm}(x,t)\| \tag{4.8}$$

In order to produce these phenomena, computational model of the hippocampus executes an optimization process, which minimizes the objective cost function. The objective cost function deals with different pattern features capturing best/worst memories and best/worst fitting memory pattern with WM[94].

$$U_{resp}(x,t) = \max_{t} U_{ltm}(x,t) \tag{4.9}$$

$$epi_{resp}(t) = \underset{x}{argmax}\, U_{resp}(x,t) \tag{4.10}$$

Response of the computational hippocampus model is retrieved from dynamic neural field $U_{ltm}(x,t)$ of the episodic (LTM) memory. For this operation, projection of the field $U_{ltm}(x,t)$ is used in equation (4.9) with respect to time (t) such that the score of the interaction history (episodic) performance $epi_{resp}(t)$ can be computed by equation (4.10) for the long-time span memory in the computational hippocampus model [94].

4.2.4 Basal Ganglia For Action Selection

As a part of limbic system in the human brain, the basal ganglia (Figure 4.11) is strongly connected with the cerebral cortex regions such as the thalamacortical, the sensory-motor cortices, the frontal lobe areas (e.g., prefrontal/orbitofrontal cortex), and other brain areas [6, 46]. It is composed of a group of nuclei, including substantia nigra, striatum, subthalamic nucleus, globus pallidus external/internal with their short acronomies SNr, SNc, Str (D1 and D2), STN, Gpi, Gpe, respectively[46, 102].

From Snc to D1 and from Snc to D2 provide two major pathways, a direct and an indirect. As a reinforcement component of the basal ganglia, the substantia nigra compacta is a neural sub-nucleus which excites D1, while inhibiting D2 [46, 102]. The region subthalamic nucleus is a main excitatory area, which receives direct state information on motor commands. The neural population region Gpe responsible for inhibiting Stn and Gpi is involved mostly in performing action-selection tasks through region Snr[12].

There are two output command signals (BS, Th) and four input signal sources (BN, AC, MC, Sub). Output terms BS, Th indicate brainstem components (midbrain, medula, VTA etc.) and thalamus. Input terms show basal nucleus (BN) from amygdala, associative cortex (AC) from prefrontal/orbitofrontal cortex, motor cortex (MC), subiculum (Sub) from hippocampus [46, 102].

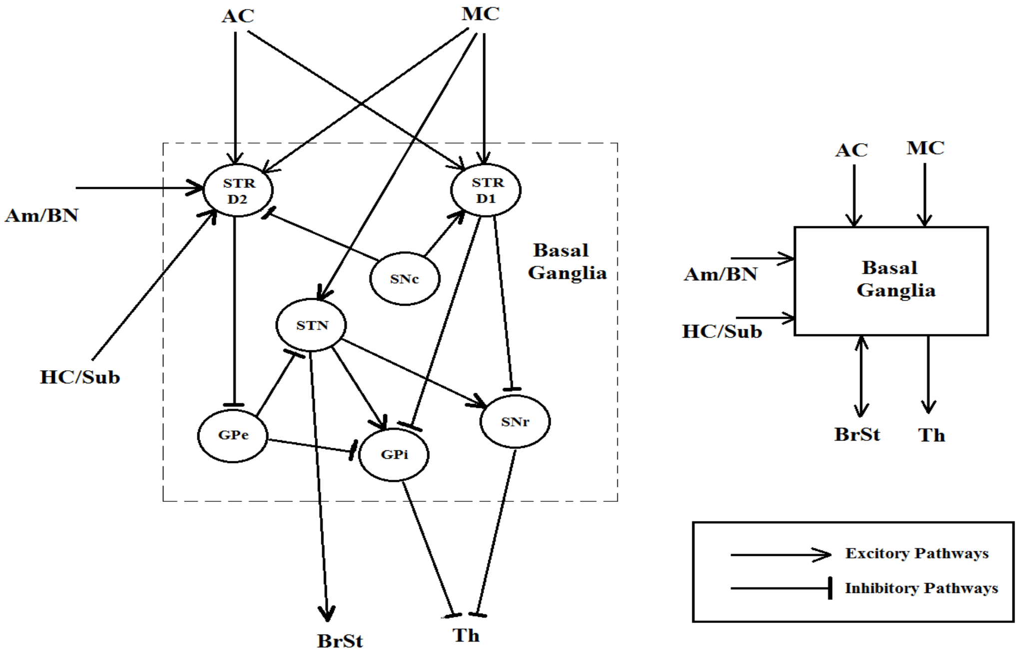


Figure 4.11 : Neural architecture of Basal Ganglia Module.

An example of spiking pattern, which belongs to neurons in regions of the basal ganglia, is shown in left-top of figure 4.12. With each time frame, firing rates of population activity can change as shown in left-bottom of the figure. Densities of firing rates, which belong to neurons in regions of the basal ganglia, are depicted in right-top of the figure. Right-bottom plot shows membrane potentials of the neurons in basal ganglia.

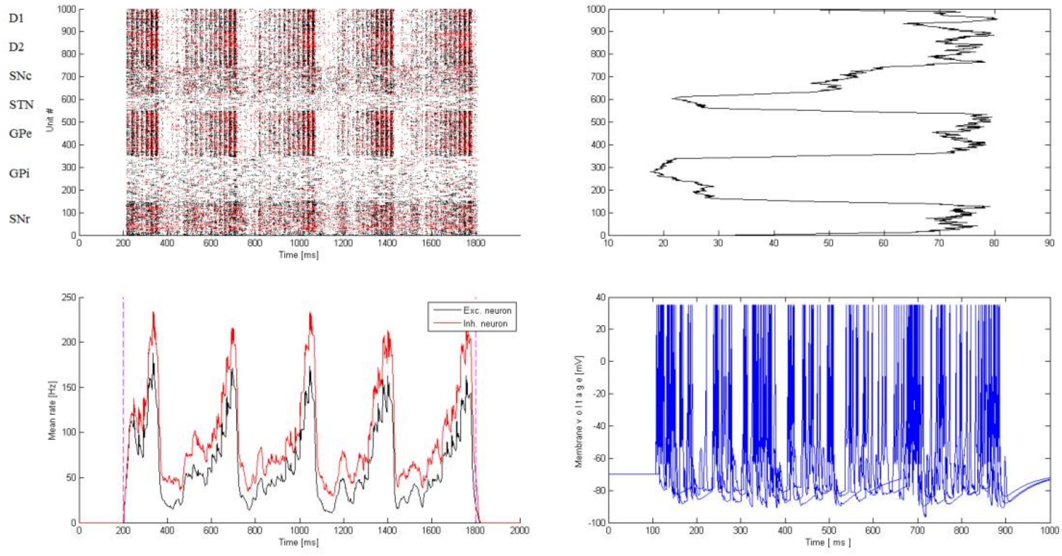


Figure 4.12 : Stochastic neural dynamics in Basal Ganglia.

The basal ganglia is involved in several cognitive skills: voluntary motor control, procedural learning related to routine behaviours or repetitive (habitual) movements

[12]. More specifically, the basal ganglia exert an inhibitory or excitatory influence on a number of motor systems. Releasing inhibition (excitation) allows a motor system to be activated. Thus, the basal ganglia is primarily responsible for behaviour adaptation patterns (action selection sequences) [102]. The computational basal ganglia model (Figure 4.13), utilizing a reinforcement learning technique [79], provides an optimal motor plan (policy) or action sequence supported by emotional rewards from the amygdala and episodic input on past interactions from the hippocampus [94].

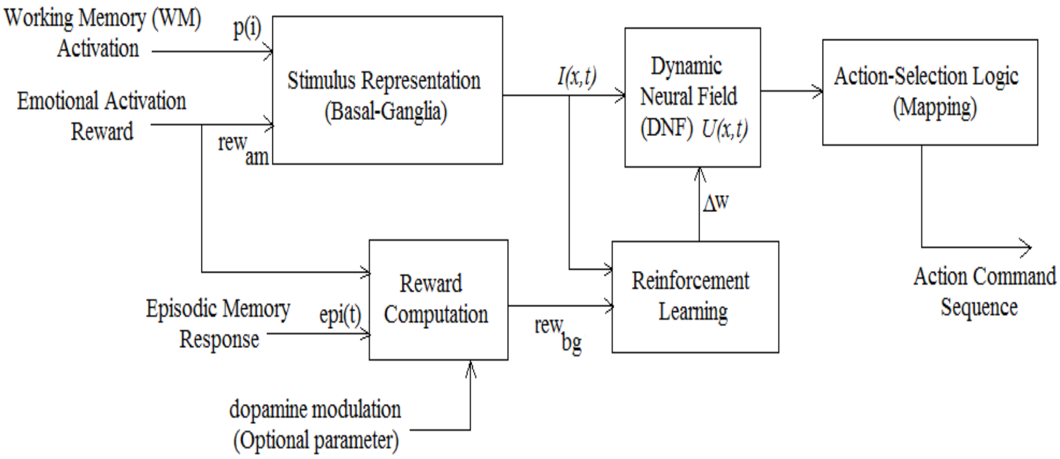


Figure 4.13 : Computational model of basal-ganglia for action selection.

In the computational model of the basal-ganglia, the stimulus activation $I_{BG}(x,t)$ is a two dimensional gaussian form, where$x = (p, rew_{am}) \in \mathbb{R}^2$. This activation feeds into the dynamic neural field $U_{BG}(x,t)$ of the basal-ganglia. The field $U_{BG}(x,t)$ allows determination of internal states for action selection. In experiments, we proposed four states according to regions $x = (x_1, x_2)$ of the field $U_{BG}(x,t)$.

$$s_{bg} = f_{bg}(x_1, x_2) = \begin{cases} s_1, & x_1 \geq 2 \ and \ x_2 \geq 0{,}75 \\ s_2, & x_1 < 2 \ and \ x_2 \geq 0{,}75 \\ s_3, & x_1 \geq 2 \ and \ x_2 < 0{,}75 \\ s_4, & x_1 < 2 \ and \ x_2 < 0{,}75 \end{cases} \tag{4.11}$$

In order to extract the states s_{bg} over $U_{BG}(x,t)$, the borders of the regions are determined by the mapping function f_{bg}. The numerical values for the equations (4.11), (4.12) are experimentally chosen in trial and error fashion[94]. Dynamic neural field $U_{BG}(x,t)$ of the computational basal-ganglia model is trained via reinforcement learning [79].

$$rew_{bg} = \frac{dp}{\sqrt{(4 - rew_{am})^2 + (1{,}5 - epi_{resp})^2}} \tag{4.12}$$

The reinforcement reward can be computed by equation (4.12). Additionally, the term dp is an optional parameter so that dopamine modulation can tune the learning progress. Reinforcement learning process modifies procedural (related to action-selection skills) memory which is stored in the weight matrix [94].

$$a_{bg} = f_{bg}(x_1, x_2) = \begin{cases} a_1, & s_{bg} = s_1 \\ a_2, & s_{bg} = (s_2 \text{ or } s_3) \text{ and } x_1 \leq -x_2 \\ a_3, & s_{bg} = (s_2 \text{ or } s_3) \text{ and } x_1 > -x_2 \\ s_4, & s_{bg} = s_4 \end{cases} \qquad (4.13)$$

A set of pre-defined actions act = {a_1 =[“clapping”, ”salute”], a_2 =[“arm shake”, “head shake”], a_3 =[“opening two arm”], a_4 =[“hide face”, “look to ground”]} is produced by the motor cortex module. Action-selection logic utilizes the states s_{bg} of basal-ganglia to make a suitable decision as feedback action [94].

4.2.5 Motor Cortex

As a module of frontal lobe sub-architecture, computational model of Motor Cortex module (Figure 4.14) which is a part of general computational brain inspired and emotion imitated cognitive framework, is responsible for the planning, control, and execution of voluntary movements [6]. The motor cortex module is composed of several main parts including primary motor cortex, premotor cortex, the supplementary motor area, posterior parietal cortex [46].

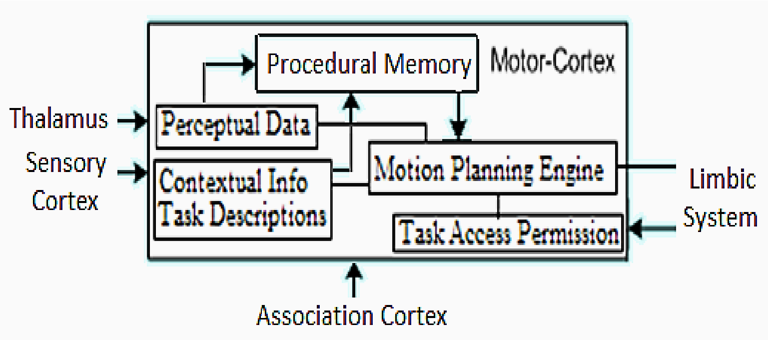


Figure 4.14 : Motor Cortex model.

The primary motor cortex providing access permission to motor commands is the major contributor to emerging neural impulses that pass down to the brain stem through spinal cord and control the execution of movement [46]. The premotor cortex involves in movement, the sensory guidance and direct control of movement. Many different task primitives generate complex behaviours in the premotor cortex. The supplementary motor area (SMA) provides the internally generated planning of sequential movement. This sub-module working as motion planning engine, includes a unique algorithm, which constitutes a probabilistic dynamic programming methodology. The posterior parietal cortex (PPC) is responsible for constructing mapping between multisensory information into motor commands. In addition, PPC includes task descriptions and perceptual data. It has large-scale connections with prefrontal regions and sensory regions like visual, auditory and somatosensory for perceptual association. Motor Cortex module has also a part of procedural memory involved in motor skills. Motor Cortex accepts feature data from sensory cortex and thalamacortical areas. Particular motor systems (e.g. body control, arms, legs and head/face) are modelled as cortical maps in the Motor Cortex.

4.3 Implementation

Certain preliminary concepts about the robot's perceptual environment, its motor (action) environment, world modelling, and its internal dynamics must be defined in order to explain the applied scenario. Some observed perceptual states are derived by events and perceptual items (e.g., face, skeleton), and they are detected, recognized, tracked, and localized for attention modelling. In the sample scenario, the robot's task planning workload can be performed in different stages [103]. Some tasks consist of basic structures, whereas others are more complex, including more than one observation and/or action state. The robot's observations may include perceptions, such as detected face or skeleton to capture movements. Then these movements can be identified as labels of the gestures for recognition progress in the cognitive perception modules. Actions of the robot including gestures are produced in the motor cortex module and transferred to motor commands.

The emotion- and motivation-based control paradigm, driven by computational limbic system architecture, regulates behaviour and monitors task performance enabling the robot to reach optimal goal states. This methodology can be integrated into predefined scenarios. In the experiments, a robot and child play several interaction games. These games are realized in turn-taking form for testing the hypotheses. According to the level of preschool children, interaction games are chosen as "peek-a-boo", "just imitate", "getting to learn our body", and "stand-up, sit-down". In the "peek-a-boo" game, the robot introduces an environment to the child for orientation. Moreover, an imitation game "Just imitate" is considered to measure response times and accuracy of the performed gestures. In “getting to learn our body”, the robot intends the child to show some parts of its body and vice versa. The last game considered in this study is “stand-up, sit-down” which requires giving spontaneous commands from robot to child. Observation states are linked to motor (action) commands by internal tasks, which humanoid robot reaches through optimal goal state procedures.

Table 4.1 : Internalstates in the scenarios.

Event No.	Action Sequence	Emotional Responses	Episodic Memory
1	clapping, salute	Happy,Relaxed,Excited	Happy,Making Small Errors
2	hiding face	Sad,Depressed,Anger	Sad,Making Large Errors
3	look to ground	Fatigued, Calm	Passive, Low Time Performance
4	clapping	Stressed, Excited	Active, High Time Performance

For example, if the robot does not recognize an expected gesture, the emotional state of the robot goes through “unpleasant” (or “sad”). Its emotional state slightly becomes “unpleasant” (or “sad”), if its recognition error is increasing. In addition, if the speed of the performed gestures is slowing as the robot is in the emotional state “unpleasant”, the robot gets to the emotional state “depression” (inhabitation state)”. If the response time is decreasing as the robot is in the emotional state “unpleasant”, the robots get to the emotional state “anger”.

Moreover, if the robot recognizes an expected gesture, the emotional state of the robot goes through “pleasant” (or “happy”). Its emotional state slightly becomes “pleasant” (or “happy”), if its recognition error is decreasing. In addition, if the speed of the performed gestures is increasing as the robot is in the emotional state “pleasant”, the robot gets to the emotional state “excited” (“excitation” state)”. If the response times is increasing as the robot is in the emotional state “pleasant”, the robots get to the emotional state “relaxed”.

4.3.1 The Experiments

Participants of the experiments are chosen from the group of preschool children with ages between three and five years. Size of the group is sixteen. The group includes 10 children with normal attention level. The others are diagnosed as ADHD. In addition to this, a teacher, psychologist and the researcher have participated to experiments.

According to these conditions, two main experiments are conducted.

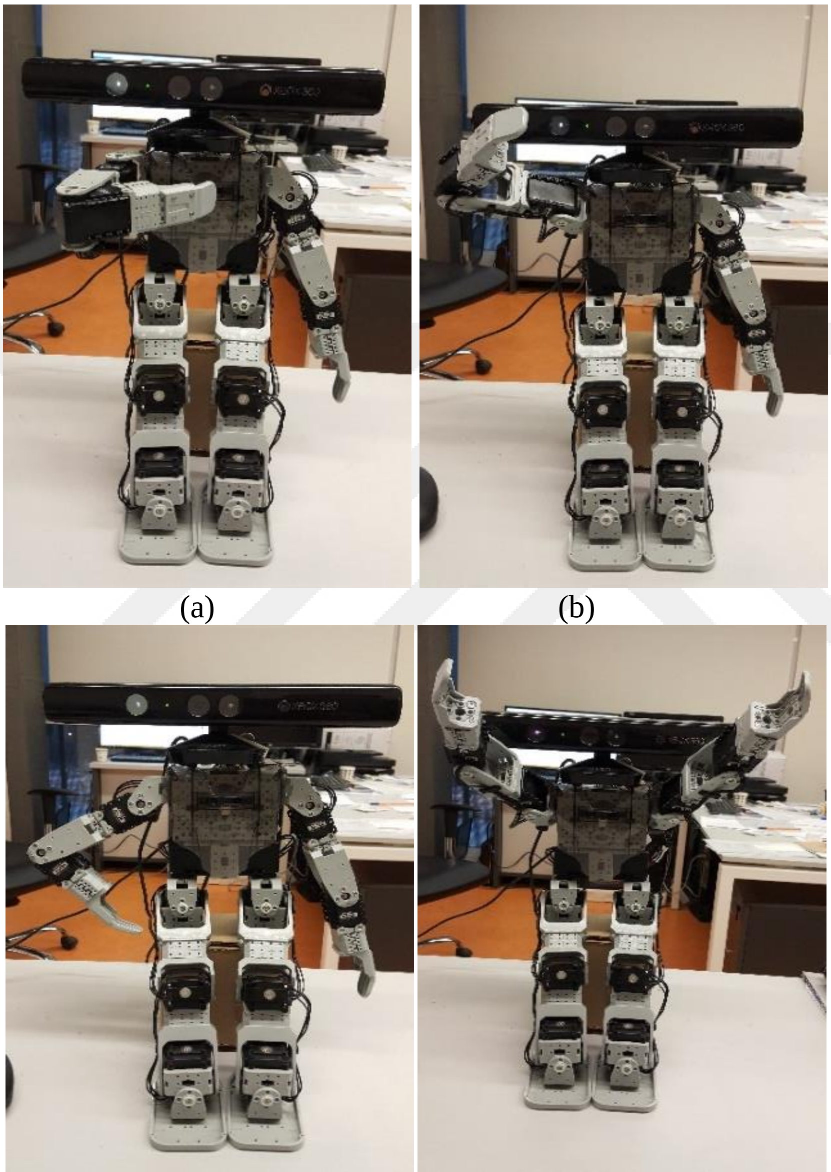
Experiment 1: In the first experiment, robot and normal group children play several interaction games. Before this stage, teacher and robot perform the interaction games sequentially. In this case, role of teacher is active (demonstrator), and humanoid robot is passive (observer). The humanoid robot records this interaction including some indicators (e.g. gesture errors and time delay of the responses) of the events. In the other case, humanoid robot is active (demonstrator), and a child who belongs to normal group is passive (observer). While it is executing turn-taking interaction games, optimal action sequences are realized as feedback, which have been learned from previous stage.

Experiment 2: The humanoid robot and group of children diagnosed as ADHD play several interaction games in the second experiment. As before, teacher and robot perform the interaction games sequentially. In this case, role of teacher is active (demonstrator), and humanoid robot is passive (observer). The humanoid robot records this interaction including some indicators (e.g. gesture errors and time delay of the responses) of the events. In the other case, humanoid robot is active (demonstrator), and a child who belongs to normal group is passive (observer). While it is executing turn-taking interaction games, optimal action sequences which have been learned from previous stage are applied as feedback.

At the end of the experiments, robot reports learning and interaction statistics. Under supervision of a psychologist, levels of rehabilitation and contribution of the neuro-cognitive architecture embodied in the humanoid robot are eleboratively discussed.

4.3.2 The Scenario

In the interaction scenario, the humanoid robot performs several gestures (Figure 4.15) according to the executed task (game) [94]. For the “stand-up, sit-down” game, there are two gestures of the humanoid. For the game “getting to learn our body”, the humanoid robot displays gestures labelled as “show your chest”, “show your head” and “show your leg” in the figure 4.15.(a)(b)(c). During the game “imitation”, the humanoid robot performs some gestures (e.g. “arms up” gesture in the figure 4.15.(d)) to be realized by the child [94].



(a) (b) (c) (d)

Figure 4.15 : Gestures of the humanoid : a) “body”, b) “head”, c) “leg”, d) “arms up”.

In figure 4.16, snapshots of a basic “peek-a-boo” activity are presented during laboratory tests [94]. The humanoid robot’s vision system accepts visual data from the Kinect sensor. Then visual data, including RGB and depth images, are transferred to the thalamus module. In the thalamus module, some preprocessing tasks like feature extraction are executed allowing the humanoid robot to detect a face. When the robot is hiding its face, it can not detect any face. On the other hand, if a human does not hide his/her face, the humanoid robot can easily detect a human face.

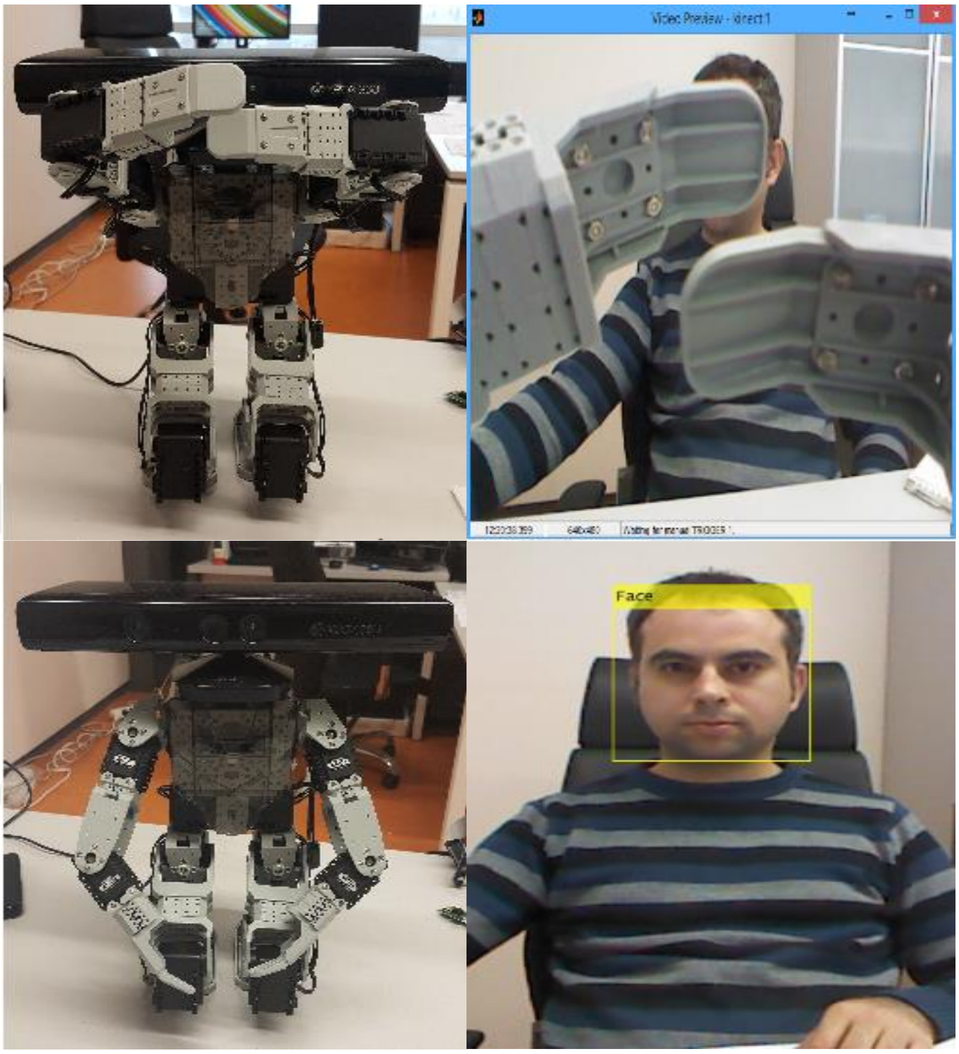


Figure 4.16 : Snapshots from the experiment.

Participants in the experiments are chosen from the group of preschool children aged between four and six years. Size of the group is sixteen. The group includes 10 children with normal attention levels, while the other six are diagnosed ADHD. In addition, a teacher, a psychologist and the researcher participated in the experiments. During the experiments (Figure 4.17 and Figure 4.18), preschool children play the simple games with respect to the sequential flow of the interaction scenario [94]. While the children are playing the games, the humanoid robot evaluates its emotional states and episodic memory inferring the attention (e.g. focused, sustained) levels of the children from interaction performance. Then, the process of action-selection are executed according to emotional and episodic memory activations [94].

Figure 4.17 : Experiment 1.

Figure 4.18 : Experiment 2.

4.4 Experimental Results and Performance Evaluation

Emotional states produced by activities of the neural field are represented in figure 4.19. Accordingly, there are two emotional states with different levels of activity in the cortical space. An emotional state located in parametric position [0.6 0.6] of the cortical region corresponds to the emotional label “excited.”

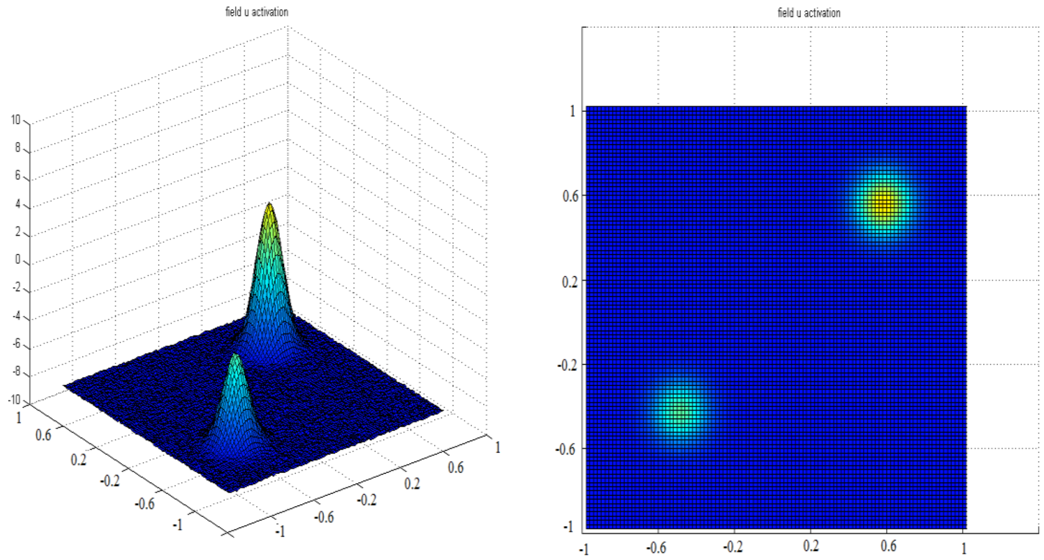


Figure 4.19 : Representation of emotional states by activities of the neural field.

The other emotional state, which is a lower-field activity, is located in the parametric position [-0.5 -0.4] of the cortical region, and it is expressed by an emotional label “depressed” (or inhibited). Larger-field activities are represented by dominant emotional expressions. Moreover, wider field activities are denoted as higher-emotional attention involving a larger neuron population.

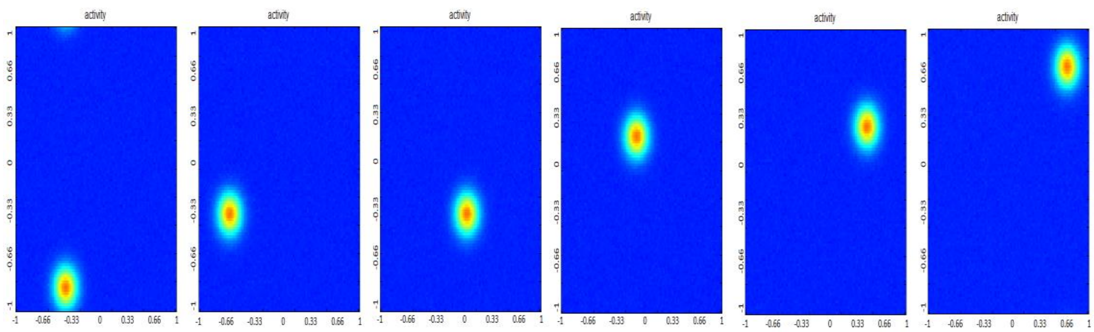


Figure 4.20 : Variations of emotional field activity.

An emotional response is shown as a wave packet, in figure 4.20. According to this, field activity related to an emotional state starts from a point [−0.89 −0.38], labelled as “depressed” and travels through a point [0.82 0.82], labelled as “excited”. In each field activity, rewards are continuously computed via adrenalin and dopaminergic gain.

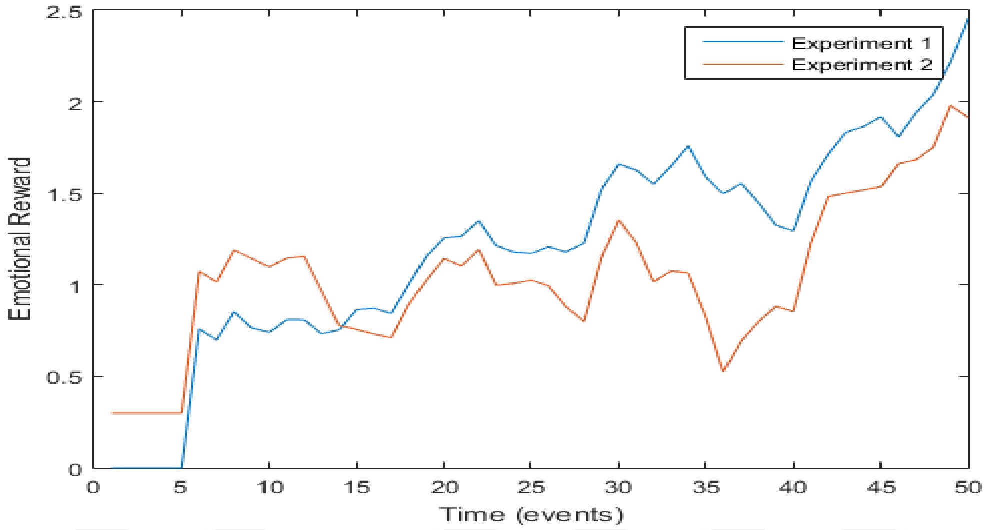


Figure 4.21 : Variations of emotional reward.

The emotional reward (rew_{am}) is computed by equation (4.3) and variations of it are observed for each event. This metric corresponds to focused attention of the preschool children. Thus, if the emotional reward is increased, the interaction level based on the children's focused attention is increased according to hypothesis (H1). In figure 4.21, the blue line indicates experiment 1 and the red line indicates experiment 2.

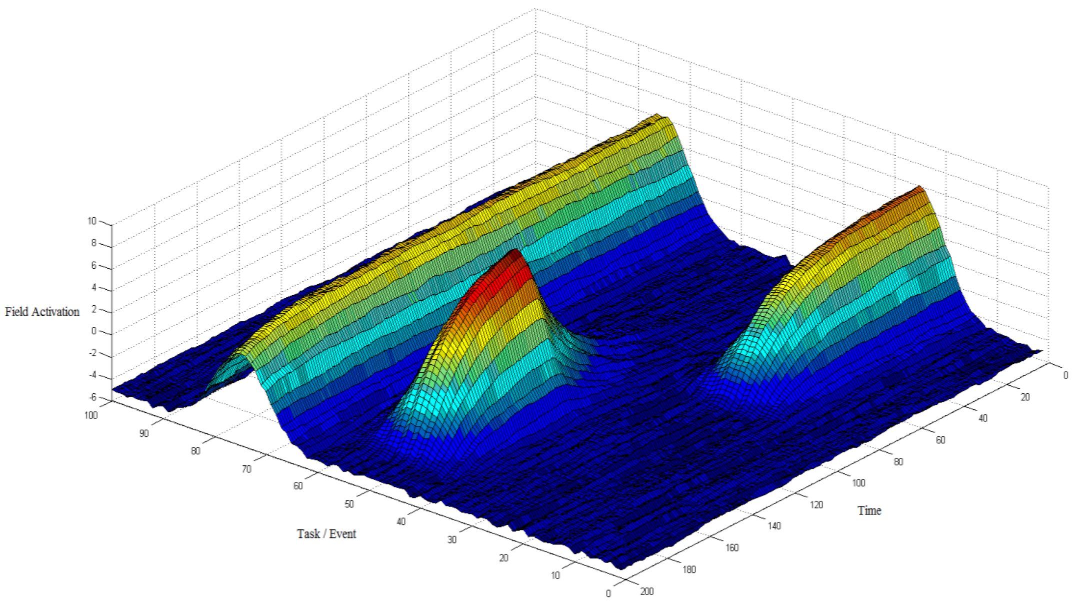


Figure 4.22 : Episodic memory representation generated by neural field activations of Hippocampus.

Observed events or executed tasks as episodic memory fragments (e.g. fired wavelets) generated by activities of the neural field are represented in figure 4.22. Accordingly, three wavelets with different levels of field activity are produced in the hippocampal memory space [94]. The episodic memory formation in the hippocampus is presented in figure 4.23. As a neural field, the feature space (horizontal axis in figure 4.23) of episodic memory passed from working memory corresponds to a scale indicating from low performance to high [94].

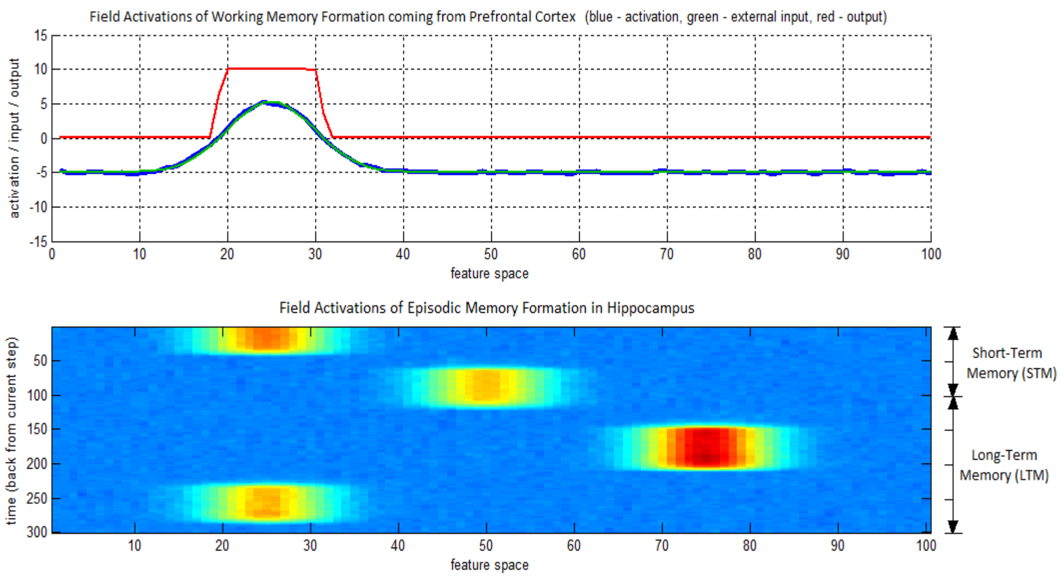


Figure 4.23 : Neural field activations of episodic memory formation in hippocampus.

The interaction performance $p(t)$ in WM and episodic response $epi_{resp}(t)$ in LTM are computed by equations (4.4), (4.10) respectively. These metrics observed for each event are related to sustained attention of the preschool children. Thus, if the success rate (or frequency) in the sequence of events (gestures to be perceived) for LTM is increasing monotonically, the interaction performance score is increased and interaction based on sustained attention is increased between the humanoid robot and preschool children according to hypothesis (H2). Also it is observed that differences between $p(t)$ and $epi_{resp}(t)$ in experiment 2 are greater than the ones in experiment 1. In figure 4.24, the top plot indicates experiment 1 and the bottom plot indicates experiment 2.

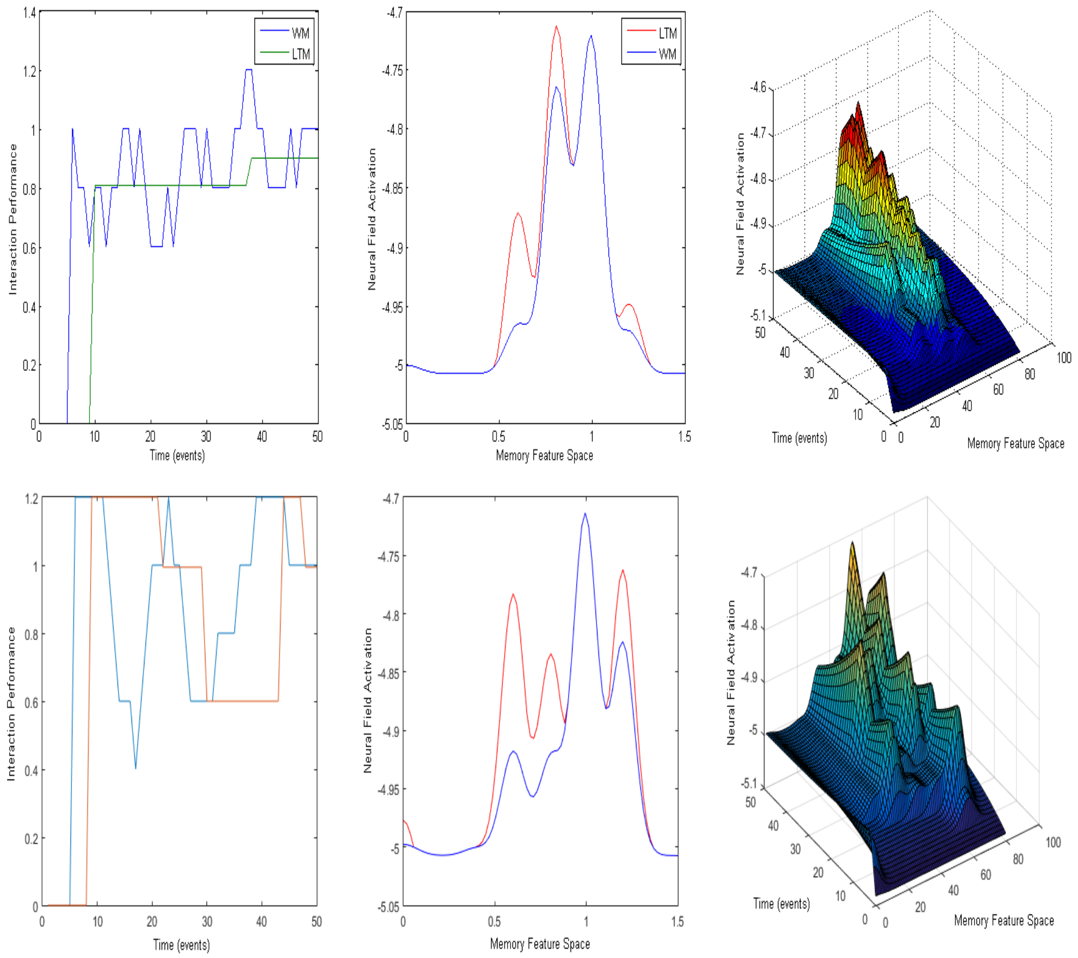


Figure 4.24 : Interaction performances observed from the neural field activations of episodic memory.

In the experiments, some turn-taking interaction games are sequentially performed (e.g., peek-a-boo, just imitate, getting to learn our body and stand-up, sit-down) between a humanoid robot and preschool children. Referring to the analysed hypotheses (e.g., H1, H2), the focused and sustained attentions of preschool children are tested under supervision. In the tables below, indicators for performance evaluation are average response time and ability score for a performed activity. The ability scores are computed as “achieved activity / total activity in a task”. The hypothesis H1, related to sustained attention, corresponds to achieved activity. The hypothesis H2, related to focused attention, corresponds to durations of the activity responses [94].

Table 4.2 : Activities with human expert.

Event No.	Interaction (Task)	Activity Log (Teacher)	Activity Log (Children)	
			Normal	ADHD
1	Peek-a-Boo	10 times - 1.2 sec	8/10 – 1,4 sec	5/10 – 1,7 sec
2	Stand-Up, Sit-Down	10 times - 1,8 sec	7/10 – 2,0 sec	6/10 – 2,4 sec
3	Just Imitate	10 times - 2,6 sec	6/10 – 2,8 sec	4/10 – 3,6 sec
4	Getting to learn our body	10 times - 3,4 sec	5/10 – 4,1 sec	3/10 – 5,4 sec

The performance scores in the activities are presented in tables 4.2 and 4.3. Accordingly, human activity logs are examined for the two groups, the normal group and the group of Attention Deficit Hyperactivity Disorder (ADHD). These experiments are conducted separately, not only with the humanoid robot but also with a human expert (e.g. supervisor or teacher) for comparative purposes. In table 6.1, the human expert has performed an interaction game play including basic tasks with the tasks being repeated several times. Meanwhile average response times were recorded. Accordingly, the preschool children as experiment groups realize tasks based on given commands from the human expert. The normal group of children are more successful with respect to the children suffering from ADHD. Also a one-way ANOVA test was performed on the four common tasks to highlight the differences between the normal and ADHD groups. The result of the ANOVA test showed that the variances in normal and ADHD groups had a significant effect ($F = 6.47$, $p = 0.0075$ with $p < 0.05$).

Table 4.3 : Activities with humanoid robot.

Event No.	Interaction (Task)	Activity Log (Teacher)	Activity Log (Children)	
			Normal	ADHD
1	Peek-a-Boo	10 times - N/A	9/10 – 2,0 sec	7/10 – 2,1 sec
2	Stand-Up, Sit-Down	10 times - N/A	8/10 – 2,2 sec	6/10 – 2,4 sec
3	Just Imitate	10 times - N/A	6/10 – 3,5 sec	5/10 – 3,9 sec
4	Getting to learn our body	10 times - N/A	6/10 – 4,0 sec	4/10 – 4,4 sec

In table 4.3, as before, the humanoid robot has performed an interaction game play including basic tasks. Average response times were recorded while these tasks were repeated several times. The preschool children experiment group including the normal group of children and children suffering from ADHD realize tasks according to given commands from the human expert. The correspondent levels of the children’s interaction based on attention across both groups appeared to be better than the previous experiment. The same statistical analysis was performed with an ANOVA test to examine the activities with the robot. The result showed that it also had a significant effect on activities with robot of the four common tasks ($F = 10.91$, $p = 0.001$ with $p < 0.05$).

In order to verify proposed hypotheses, a statistical analysis is performed on both groups for all tasks. Also a paired sample *t* test was performed on the four common tasks for all children in the normal group. The variances of achieved activity between human and robot had a significant effect ($t = 3.94$, $p = 0.0153$ with $p < 0.05$). Also the variances of response times between human and robot had a significant effect ($t = 2.62$, $p = 0.0275$ with $p < 0.05$). Therefore, the result of tests showed that hypothesis 1 and hypothesis 2 are verified for the normal group. The same statistical analysis was performed with a paired sample *t* test on the four common tasks for all children in the ADHD group. The variances of achieved activity between human and robot had a significant effect ($t = 2.49$, $p = 0.0258$ with $p < 0.05$). Also the variances of response times between human and robot had a significant effect ($t = 6.47$, $p = 0.0211$ with $p < 0.05$). Therefore, the result of tests showed that hypothesis 1 and hypothesis 2 are verified for the ADHD group.

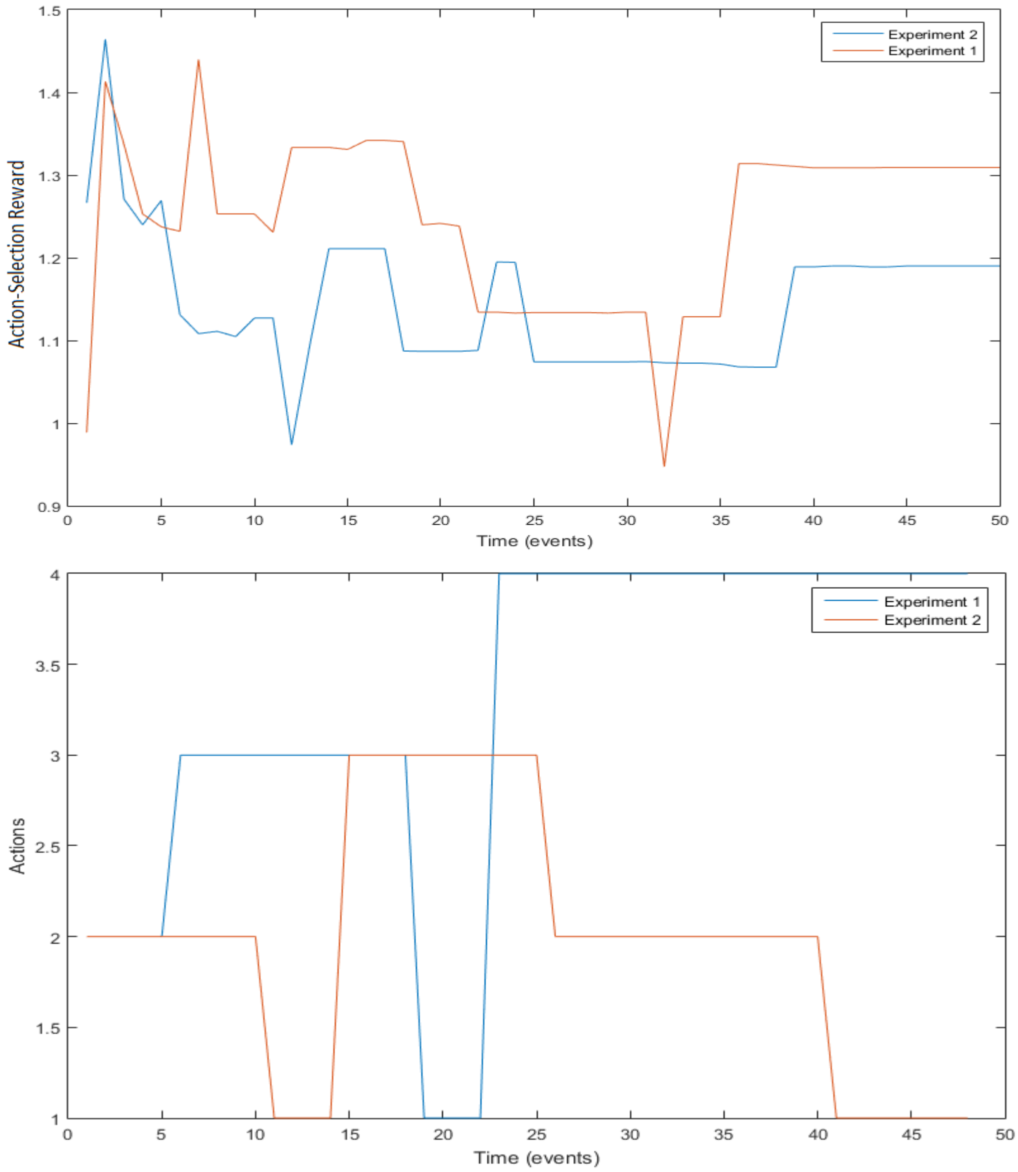


Figure 4.25 : Action selection rewards and executed reward actions.

According to the hypothesized scenarios, the learning process of the action-selection is performed using the reward mechanism described in equation (4.12), producing the optimal sequence of motor commands in the basal ganglia [94]. While the basal ganglia is operating action-selection tasks via the reinforcement learning procedure with a reward coming from amygdala, various action-selection sequences are observed in the experiments. During the experiments, reinforcement learning activities that shape procedural (a memory related to action selection skills) memory in the computational model of the basal ganglia and executed reward actions are presented in figure 4.25. The bottom plot of the figure corresponds to action indices $\{a_1 = 4$, $a_2 = 3$, $a_3 = 2$, $a_4 = 1\}$.

Table 4.4 : Training performance comparisons.

Computational Neural Model	Amygdala (Reinforcement Learning)	Hippocampus (Unsupervised Learning)	Basal-ganglia (Reinforcement Learning)
Dynamic Neural Field	% 76,21	% 63,89	% 72,53
Neural Mass Model	% 71,03	% 56,42	% 68,47

Performance comparisons of computational mechanisms used in the architecture are presented in table 4.4. These comparisons are performed in different modules (amygdala, hippocampus and basal-ganglia) through various learning approaches. For the amygdala and basal-ganglia modules, reinforcement learning performances of two computational mechanisms (dynamic neural field and neural mass model) are observed while unsupervised learning performances are observed for the hippocampus model of the architecture[94].

Table 4.5 : Comparision of rehabilitation rates.

	Human Expert (Teacher)	Humanoid Robot (Brain-Inspired Neuro-Cognitive Architecture)
Normal Group	2,52	2,47
ADHD Group	1,37	1,71

The rehabilitation rates of the attention deficit hyperactivity disorder (ADHD) problem are recorded in the confusion matrix for the humanoid robot's cognitive architecture. The values in table 4.5 correspond to the mean performance scores in table 4.2and table 4.3. They were computed by a formulation: sum of achieved activities / sum of response times in the columns normal group and ADHD. Accordingly, increased rates show the success level of the rehabilitation progress. If interaction between the humanoid robot and normal group children is investigated, it is shown that there is little performance gap with respect to children suffering from ADHD, while the performance gap of interaction with the human expert is greater [94].

5. CONCLUSIONS AND RECOMMENDATIONS

5.1 Pratical Applications and Impact

In this thesis study, the major impact is to construct a computational framework for a humanoid robot which can be employed in the assistive and rehabilitation case studies involving primarily social, developmental and physical interaction (e.g. motion disabilities) [94]. For rehabilitation studies, deliberative decision making processes and ability to perform complex behaviour sequences are required [6]. In addition, associative learning abilities and emotional expressions could be helpful for these application purposes.

According to the interaction between robot and human, various different scenarios can be implemented where the robot has a special role such as a personal assistant or therapist [94]. In terms of application areas, utilizing “humanoid robots embodied computational brain inspired neuro-cognitive architecture” will be realized in some pilot studies such as households, schools, hospitals and other rehabilitation centers. This thesis provides major contributions to HRI studies such as brain inspired computational modelling of the cognitive perception system and the limbic system for a humanoid robot. Our proposed computational architecture handles interaction problems based on the joint attention task. Within this thesis a spatio-temporal cognitive perception system inspired by brain’s perceptual mechanism for a humanoid robot, is developed and presented in chapter 3. A computational limbic system realizing emotion and episodic memory based control is constructed and realized in the chapter 4. In addition, an action selection mechanism is modelled for this architecture.

Dynamical interactions between human and autonomous humanoid robots with computational brain inspired cognitive architecture are investigated and analysed from the viewpoint of contribution to society and scientific development [94]. Records of the responses acting on subjects (humans) to the humanoid robots are stored in a database. Finally, results of scientific discoveries are reported with detailed discussion.

5.2 Discussion

The proposed "interaction based on joint attention tasks using a humanoid robot platform with brain-inspired neuro-cognitive architecture" is a novel approach to the best of our knowledge. As a computational framework, the proposed system consists of two sub-architecture named limbic system and cognitive perception system.

In the presented thesis, the computational model of a human brain's limbic system and perceptual system embodied in a humanoid robot are tested. The robot undertakes multiple objective task planning problems under predefined interaction scenarios until it reaches the optimal goal state. This robot control architecture is based on the neuromorphic foundations of the behaviour selection mechanism, which are driven by emotion and episodic memory. The new computational framework is embedded into a humanoid robot platform the Bioloid robot. In addition, a reinforcement learning-based adaptation procedure is applied on the separate regions of the computational limbic system (e.g., basal ganglia, hippocampus, and amygdala) to train behaviour selection procedures. Emotional responses and behavioural transition events are perceived during simulation. The cognitive perception system which cognitively process perceptual responses, forming environmental awareness, and allowing perceptual behaviours (e.g. focused attention) is a framework of overall neuromorphic cognitive architecture employing a group of computational models. Dynamic neural field model utilized in the limbic system provides an efficient computational mechanism to represent the cognitive activities of the humanoid robot. Additionally, a neural mass model is utilized as a comparative method employing population dynamics of artificial neurons instead of field dynamics of the neural system. There is little resultant difference in training scores. According to results of performance comparison, the dynamic neural field model is slightly more effective than the neural mass model.

This architecture presents an approximate computational solution which is based on the perceptual regions in human brain. The system is composed of several cortical regions including thalamus, sensory cortex (e.g. occipital lobe (visual cortex), temporal lobe (auditory cortex), parietal lobe (somatosensory cortex)). As a function of temporal lobe, recognition processes are realized by supervised learning methodology using extracted feature data of stimuli under the supervision of semantic memory. Parietal lobe is responsible from constructing environmental model and interpreting spatial awareness for a humanoid robot. Also the system has its own attention mechanism which can be called as perceptual attention. According to the data coming from input stream (thalamus) and supervision data coming from semantic and episodic (long-term) memory, sensory cortex executes cognitive perception tasks by its computational model. In our proposed system architecture, several machine learning method shave been employed such as naïve Bayes, k-nearest neighbours (k-NN), decision tree, support vector machine (SVM), feedforward neural network (multi-layer perceptron (MLP)) and convolutional neural network (CNN or ConvNet). Comparison of these methods depicts the effectiveness of the computational cognitive perception system, which realizes related perceptual cognitive skills for a humanoid robot.

The interaction scenario is tested in a MATLAB environment. In this work, current task requests, released from the working memory, and past task requests, released from the episodic memory in the hippocampus, indicate that according to the produced emotional response, a behavioural reward is applied to select the optimal action commands. Thus, the attention-based interaction activities of the participants increased.

5.3 Verification

Two main experiments were performed to verify the cognitive perception system and related research questions, RQ1 and RQ2 in chapter 3. RQ1 was verified since social interaction based on joint attention was established between a humanoid robot and human so that the robot may be used as an educational or rehabilitation assistant. The humanoid robot achieved human like perceptual cognition, which evaluates spatio-temporal awareness that investigates correlation between pattern recognition skills, semantic memory development and selective attention model with competitive focuses under multi-modal stimuli. So RQ2 was also verified.

In chapter 4, two main experiments were performed to verify the above proposed architecture and related hypotheses, H1 and H2. While one experiment dealt with a group of normal children, the other dealt with children suffering from ADHD. As a result, that sustained attention is observed via increased interaction scores without response times of the activities increasing, verifies that sustained attention increased (H2). It is also observed that, the response times decreased as the interaction scores increased, verifying that focused attention increased (H1). Additionally, during the experiments, differences in interaction scores and time performances were gradually decreased between the normal and ADHD groups. The presented architecture can be further improved in the future by integrating cognitive perception with brain I/O interface architecture. The results were also verified with one-way ANOVA and paired sample t tests [94]. Experimental results related to constructing perceptual infrastructure for a robot show that perceptual skills including recognition and environmental modelling are realized.

5.4 Future Works

In future studies, other interaction disorders that are out of the scope of this study will be investigated using HRI. From the viewpoint of computational infrastructure, improvement in the cognitive functions in the cortical regions (e.g. basal-ganglia, amygdala, hippocampus and hypothalamus) of brain-inspired architecture is expected. In addition, computational methods for additional tuning parameters (e.g. dopamine and adrenaline) will be detailed. The presented architecture can be further improved in the future, by integrating approximate models of the other cortical regions of brain inspired architecture. As viewpoint of computational infrastructure, cognitive functions in the cortical regions of brain inspired architecture will be improved.

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APPENDICES

APPENDIX A:

Pseudo Code of the Program Code;

```
Robot Initialization
Starting Parameters

Loop_start
        Reuest = Scenario_Menager()
        a = Task _Assign(Request)
        Action_Perform(a)

        While  (until gesture performed)
                        Stream = Thalamus ()        // Data Acqusition
                        // Obtain recognized gesture (Rec_Gest),  Gesture Error (Gest_Err)
                        [Rec_Gest, Gest_Err] = Sensory_cortex (Stream)

                        IF (Rec_Gest == a)
                                Calculate Response_time
                                Robot_say ("Correct")
                                Perf = True
                        Else
                                Robot_say ("Incorrect")
                                Perf = False
                        End_IF
        End_while

        (A, V, Reward, Emotion_state) = Emotion_model (Response_time, Gest_Err)
        (Ep_mem) = Episodicmemory_model ( A, V, Perf)
        act = Actionselection_model (Ep_mem, Reward, Emotion_state)

        Online_Datavisualization ( )
Loop_end

Terminate_program ( )
Release_memory ( )
```

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