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Artificial Limbic Brain Models Using Neural Networks for Emotional Analysis

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Abstract*:Artificial Intelligence Has Steadily Been Gaining Popularity And The Attention Of Scientists And Engineers In The Past Few Decades.AI Was Built Using Mathematical Techniques Based On Probability And Statistics Allowing Machines To Give Their Best Guess For Any Solution. However, Emotional Incorporation In AI Still Remains Vastly Uncharted. This Paper Is In Line With This Vision. It Puts Forth An Architectural Representation For Such An Emotionally Astute Intelligence By Discussing The Major Setbacks Faced While Creating A Computational Model For Emotions. It Does So By Describing The Various Ways In Which Emotions Are Mapped Artificially As Well As By Describing Biologically Inspired Predictive Models That Learn From These Mappings To Generate Vectors That Allow For Accurate Predictions. Apart From This Citations Have Been Made To Animal Cognition For Prosodic Nuances Of Speech Which May Result In Higher Sophistication Of Existing Systems To Detect Emotions***.**
Keywords*-Artificial Intelligence,Canine Neurology,Cognition,Emotional Intelligence,Limbic Brain.*

I. Introduction

Neuroscience And Psychology Have Long Been Treated As Sciences That Are Rather Isolated From The World Of Computing.However, Recent Advancements In Machine Learning Algorithms And Computational Hardware Has Caused Scientists To Bridge The Gap Between These Fields [1].This Has Caused An Evolutionary Change In The Way Traditional Computer Programs Are Written.

In Order To Solve Real World Problems, Programs Are Now Making Use Of Probabilistic Models Often Termedas Artificial Neural Networks To Account For Randomness And Variability. These Models Are Loosely Designed On The Working Of The Human Brain.

While A Number Of Well Renowned Scientists Have Been Able To Remodel A Large Aspect Of This Glorious Form Of Engineering, Yet One Of The Most Crucial And Highly Prized Aspect Of Humans Remains Starkly Distinguished From The Machines We Have Created, Our Emotions[3][4].

Emotions Are Fuzzy, They're Complicated And This Kind Of Unpredicted, Uncategorized, Highly Nested Nebula Of Labels Is A Perfect Fit For Such Predictive Models.With This In Mind We Decided To Review The Nature Of Probabilistic Predictive Models When Applied To This Subtly Differentiated Plethora Of Human Emotions.

To Do So Wehave Divided This Review Paper Into Six Distinct Sections. Section I Being The Introduction, Section II Elaborates On The Background, Section III Expands On The Proposed Methodology Which Further Sub-Contains3.1 Sensory Stimulation And Its Preprocessing And 3.2Emotional Models, Section IV Discusses The Results, Section V Concludes The Paper And Section VI Consists Of The References Cited In This Paper.

II. Background

It Is Difficult To Understand The Concept Of Consciousness And Creativity Which Sets Humans Apart.To Impart These Features To Machines, We First Need To Understand Their Root Cause In Humans Themselves.This Problem Of Imparting An Abstraction Of Characteristics To Generate Knowledge, Which Can Then Be Used For Further Understanding Of Human Emotional Psychology, Can Distinctively Be Seen As A Four-Part Process Consisting Of 1.Data Collection And Validation, 2.Pre-Processing, 3.Learning Based On Artificial Emotional Models And 4.Predicting In Previously Unseen Scenarios. Based On Our Study Of State Of The Art Publications, We Identify Emotional Models To Play A Crucial Role In Generating Efficient Results.[2][5][11]

Our Brain Consists Of The Cortical Region(Rational Thinking) And The Limbic Region (Emotional Hub).All Rational Decisions Are Made By The Cortical Region, However The Strongest And Most Crucial Decisions Are Not Only Influenced By Rational Understanding Of A Situation But Are Also Greatly Affected

By The Emotional And Environmental Factors Of The Situation And That's Where The Limbic System Comes Into Play. The Limbic System Lies Right Under The Cerebrum, And On Either Side Of The Thalamus.It Is A Complex Collection Of Different Brain Parts Which Together Function To Give The Emotional Judgement [2][11].

We Aim To Partially Reproduce The Same Characteristics As The Biological System Into A Computational Model Inspired By This Neurological Behavior.

III. Proposed Methodology

Based On This Literature Review An Architectural Model Is Presented For Such An Emotionally Adept System. This Can Be Visualized Through Fig 1.

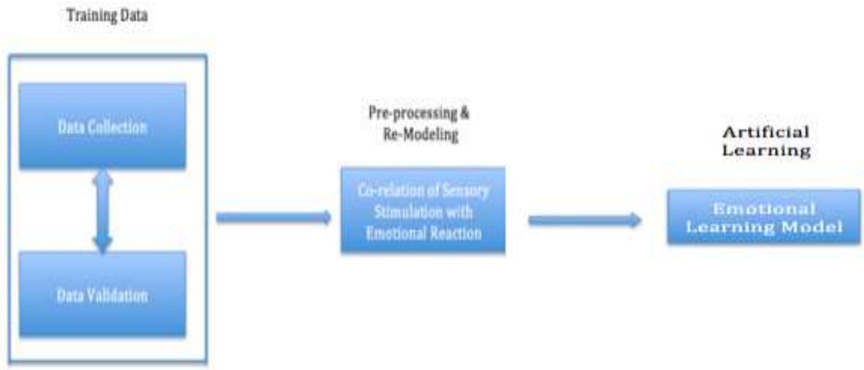

Fig. 1:Diagram Representing Architectural View Of Emotional Model.

3.1 Sensory Stimulation And Preprocessing

Literary Studies On Emotion And Cognition Indicate Their Complexity And The Inadequacy To Subjectively Quantify Them. Hence The First Key Step Is To Create An Accurate System Of Measurement. This Is Done By Describing Emotional Reactions As A Function Of Measurable Sensory Cues. Subsequently, A Number Of Studies Have Made Use Of Various Quantifiable Features To Observe Patterns And Relations Between These Features And The Emotions Experienced [1][3][4][7].

Chungk Lee And His Colleagues [3] Attempted To Measure The Variation Of Emotions As A Function Of Change In The Autonomic Nervous System (The ANS Refers To That Portion Of The Human Nervous System That Functions Without Any Conscious Thought), By Measuring The ECG And GSR Signals Of The Sample Humans. The Emotions Were Mapped To A Two-Dimensional Space Known As The Valence-Arousal Plane, Where Valence Indicates The Nature Of The Emotion (Positive Or Negative) And Arousal Indicates The Amount Experienced. These Results Were Then Used To Train A Multilayer Perceptron (MLP) Neural Network, Which In Itself Would Then Represent A Particular Emotion. The Experiment Was Performed On A Group Of Six Individuals Consisting Of Three Males And Three Females And An Estimating Rate Of 80.2% [3] Correct Prediction Was Achieved By Using This Method, Indicating That Constructing Relations Between The Describing Variables Of The ANS And Emotions Provides Reliable And Efficient Outcomes.

The Summarized Results Of The Experiment Can Be Seen In The Table Below.

Table 1: Prediction Percentage Of Trained Neural Network.

Emotion / Test	a	b	c	d
a	84.6	13	2	0.4
b	5.6	77	11.6	5.5
c	0.9	11.3	71.7	16.1
d	3.3	4.1	5.2	87.5
Total accuracy	80.2 %			

A: Sad, B: Calm Pleasure, C: Interesting Pleasure, D: Fear. [3]

While The Results Of The Designed Classifier Are Categorically Efficient It Is Primarily A Static Model And Hence Is Not Practically Scalable For Real Time Emotion Detection. Apart From This, The Model Accounts For Only Four Categories Of Emotions And Thus The Efficiency Levels Are Unclear In Case Of Larger Number Of Classes Or For Differentiating Between Degrees Of The Same Emotion.

One Particularly Interesting Way To Account For A Larger Degree Of Classification Is Done By Regenerating The Input Data In A Manner That Specifically Highlights It's Critical Components Which Will Directly Affect Emotional Understanding. This Form Of Pre-Processing Not Only Provides Features That Can Be Mapped To Emotions But Also Allows For Elimination Of Unwanted Noise Thereby Increasing Accuracy Of Prediction.

In Recent Years The Ability To Draw Unbiased Conclusions From Data Has Shown Tremendous Advancements.

Meysam Asgari And His Colleagues [4] Introduce A Method Of Prosodic And Acoustic Feature Extraction, Including Shimmer And Jitter From Speech By Employing Harmonic Models Over The Standard Existing Methods. This Was Used For Screening Adolescents With Depression Based On Speech And Spoken Utterances. Correspondingly, The Condition Of The Subjected Adolescents Were Clinically Benchmarked Via The LIFE (Living In Family Environment) Coding System. Speech Being A Non Stationary Signal Was Framed Using The Hanning Window Technique And Voiced Sequences Were Statistically Determined. Features Such As Pitch Frequency, HNR, H12, Jitter Shimmer And Harmonic Coefficients Were Approximated Apart From The Standard Features Which Were Used In Case Of The Unvoiced Segments Of Speech. These Values Were Then Used To Obtain A Per-Utterance 192 Dimension Feature Vector By Applying Standard Summary Statistics To Each Frame. This Resulted In A 74% Accuracy Which Is Sufficient For Preliminary Screening Of Depressed Individuals.[4] The Summarised Results Are Shown In Table 2.

Table 2: Comparison Of Performance Of SVM Classifier Using Different Features For Classifying Clinical Depression Of Adolescents [4].

Features	Classification Accuracy
Chance	52.4
Text	65.4
openSMILE	64.7†
openSMILE+Text	68.0†
Harmonic Model	68.7†
Harmonic Model+Text	74.0†

While These Methods Of Generating Qualitative Feature Spaces Have Been Proven To Be Efficient, They Are Unable To Account For One Of The Most Intrinsic Properties Of Human Emotion, The Continuous Nature Of Its Intensity. This Implies That There Are No Number Of Finite Dimensions Which Can Be Used To Depict The Infinitesimal Variations Ofparoxysms Of Human Emotion. In A Recent Study By Jing Han And His Colleagues [10] A Mathematical Model Is Proposed Where Emotions Are Described In The Form Of States And Their Transference Is Derived Based On Both External Stimuli As Well As And More Importantly An Emotional Intensity Attenuation Function, Which In Turn Is Defined In Terms Of Emotion Type, Stimulus Intensity And Personality.

ε: The Intensity Factor Of The External

τ Cognition Reappraisal Factor

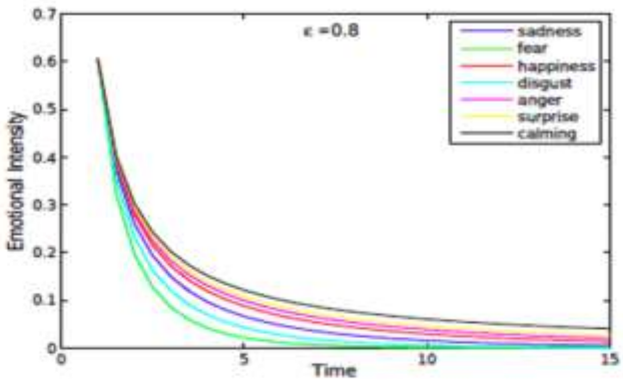

Fig. 2: Simulation Result Of Emotional Intensity Attenuation Trend Under Different Emotional States [10].

Based On Gross Emotion Regulation Model, Finite State Machine (FSM) And The Psychological Energy Theory, The Emotional State Transference Process Is Described. The Initial Values Of Emotional State Transition Probability Matrix Are Calculated By The Interaction Between Emotions. These Are Corrected By The Emotional Attenuation Function Which Is A Function Of The Cognitive Reappraisal. This Mathematical Hypothesis Was Simulated And The Results As Shown Below Validate That The Hypothesis Can Efficiently Visualize The Effect Of The Emotional Intensity On The Transitional Probability Of Emotional States.[10]

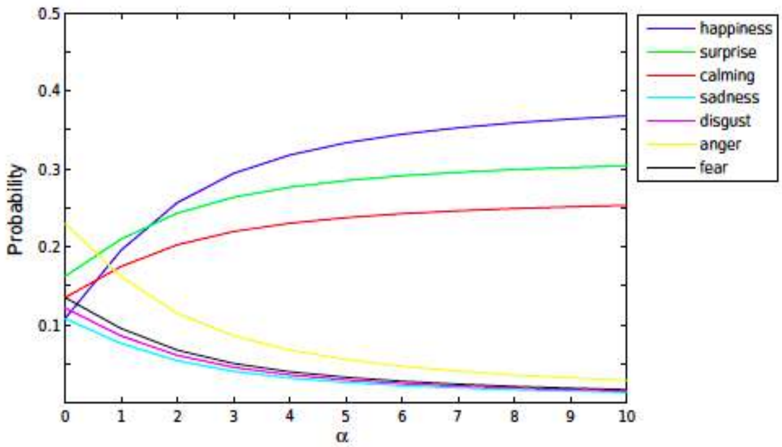

Fig. 3: Simulation Result Of Transition Probability Curve With The External Emotional Stimuli Being Positive [10].

3.2 Emotional Models

Emotional Experience Has Two Distinct Components In Human Beings: 'Automatic' And 'Attended'. Automatic Is Based More On The Ventral And Limbic Regions Of The Brain Whereas The Attention Part Is Concerned With Cognitive Aspects Of Experience, And Involves More Of The Analogous Side Of An Invertebrate(Dorsal).The Possible Dissociation Between The Cognitive And Emotional Components Can Be Studied By First Gathering Data.This Can Be Done By Using A Variety Of Methods Including Brain Imaging And Controlled Experiments Which Analyse Emotions Compared To Their Neutral Inputs.This Data Is Then Put Into A Model Engineered For Emotional Analysis.Parietal And Dorsal Prefrontal Sites Create Control Signals To Achieve Attention Focusing On A Specific Input.Using This Data The Model Reverse Engineers The Parietal Cortex And Produces The Attention Signals Which Modulate The Motor Areas.An Extension Of This Model Involves A Limbic Brain Network Having Representation For Salience And Valence.A Limbic Based Neural Network Is Thus Created For Better Feedback Mechanism.A Feedback Which Has Both Rational And Emotional Thinking [2].

The Limbic System Is A Complex System Of Different Sub Parts, Each Playing A Vital Role In Emotional Reaction And Motivation.Amygdala Is One Such Organ.It Is Responsible For Emotional Evaluation Of The Stimuli Which Is Used As A Basis For Emotional States, Reactions And Is Used To Signal Attention And Form Long-Term Memories [2][5][11].The Amygdala And The Orbitofrontal Cortex Are Connected With Two Pathways Involving The Basal Ganglia.The Direct Pathway That Has An Excitatory Influence On Cortical Activity And The Indirect Pathwaythat Has An Inhibitory Influence On The Cortex.These Connections Could Provide A Means By Which Either Positive Or Negative Emotion Could Affect The Judgments Of The Critic If Present, Which May Influence The Ideas Influenced And Retrieved [5][6].

They Use A Two Pronged Computational Model Consisting Of The Amygdaloid Part And The Orbitofrontal Cortex.The Amygdaloid Part Receives Inputs From The Thalamus And From Cortical Areas, While The Orbital Part Receives Inputs From The Cortical Areas And The Amygdala Only. A Reinforcing Signal Is Also Received By The System.The Amygdaloid Part Learns To Predict And React To A Given Reinforcer. This Subsystem Can Never Unlearn A Connection I.E. Once Learned, It Is Permanent.This Gives The System The Ability To Retain Emotional Connections For As Long As Required. The Orbitofrontal System Checks For Mismatches Between The Base Systems Predictions And The Actual Received Reinforcer And Will Inhibit The System Output In Proportion To The Mismatch.Basic Simulations Are Run To Test Features Of Acquisition-Extinction-Reacquisition, Simple Blocking And Conditioned Inhibition.We Will Discuss Acquisition-Extinction-Reacquisition And Simple Blocking.

Acquisition

In This,The Model Is Expected To Associate A Stimulus With A Reward/Reinforcer, If The Reinforcer Is Absent The Stimulus Should Disassociate, And Then Reassociate Them Again.

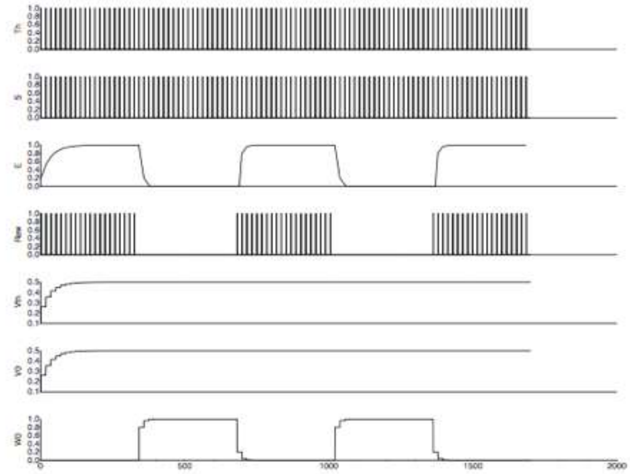

Fig. 4: Acquisition [5]

From Fig 4 We Can See That The Stimulus *S* And The Thalamic Input *Th* Occur Simultaneously And With The Same Intensity, Resulting In *Vth* And *V*0 Sharing The Responsibility For The Association To *Rew* As Can Be Seen In The Output E.When The Reinforcer Disappears, The Amygdaloid Weights Are Not Affected,Instead The Orbitofrontal Weight *W*0 Rapidly Increases And Inhibits The Output. As Soon As The Reinforcer Reappears, *W*0 Decreases To Zero, Allowing The Amygdala To Express The Previously Learned Association.

Blocking

In This Blocking Simulation We Show The Ability Of The Model Not To Associate A Stimulus With The Reinforce If There Is Already An Established Association.

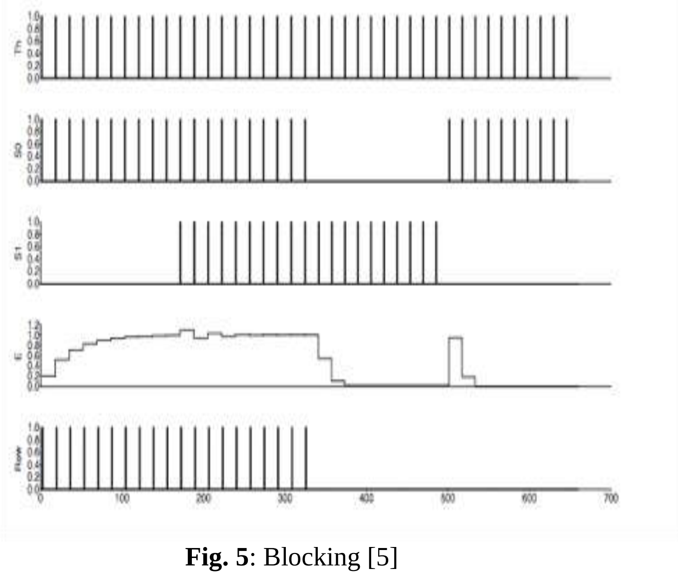

Fig. 5: Blocking [5]

This Blocking Schedule Is Run In Three Phases: First We Associate S0 With The Reinforcer, Then Present Both S0 And S1 Together With The Reinforcement, And Last, Test S1 To See Whether It Has Been Associated With The Reinforcer. We See There Is No Response To S1 In The Output E.This Is Because When The System Is Presented With S1 And Th In The Absence Of A Reward, The Orbitofrontal Part Will Learn To Inhibit A Response Through The Connection Weight For S0. These Simulations Give Results As Expected And Indicate That The Model Contains The Basic Features Needed For Associative Learning. However, The Model Is Not A Complete Learning System. The Two Most Important Missing Parts Are A Context Model And Some Form Of Motor Learning System That Can Use The Output Of This Model. The Context Model Would

Mostly Be Replacing The Orbitofrontal Inputs. A Motor Learning System Would Use The Output Of This Model As A Reinforcing Signal For Learning Motor Sequences.[5]

While Emotional Cognition Of Humans Has Been Highly Researched And Replicated, Animal Cognition And Neuroscience Has Been Relatively Ignored. A Number Of Recent Studies Have Pointed Towards Highly Sophisticated And Developed Systems Of Auditory Cognition And Correlation Of These Signals With Emotions Especially In Canines. [8][9].

As A Results Of Thousand Of Years Of Domestication, Dogs And Humans Have Shared A Similar Environment.In A Comparative Study Between Primate And Non-Primate Species, Both Dogs And Humans Were Presented With The Same Set Of Vocal And Nonvocal Stimuli.Findings Revealed That Acoustical Cues Related To Vocal Emotional Valence Are Processed Similarly In The Dog And Human Auditory Cortex.[8] Recent Advancements In Canine Neurology Has Shown That Domestic Dogs Can Perceive Dog And Human Emotions From Both Auditory And Visual Inputs. In A Cross Modal Experiment Dogs Were Shown Either Human Or Dog Faces With Different Emotional Valences (Happy / Playful Against Angry / Aggressive). This Was Paired With A Single Vocalization With Either A Positive Or Negative Valence Or Brownian Noise From The Same Individual. Results Showed That Dogs Looked Significantly Longer At The Face Whose Expression Were Compatible With The Valence Of Vocalization. Dogs Performed In This Way Without Any Prior Training And Hence Shows That These Emotional Signals Are Intrinsically Important.[9]

IV. Results And Discussion

As Per The Above Review We Find The Following Comparison Highlighting The Techniques Which Are Most Satisfactory In Each Category.

TABLE 3: COMPARATIVE STUDY OFPROPOSED ARCHITECTURES

Architectural Component	**Brief Description**	**Statistical Results**
1.Data Collection	As A Supervised Model Of Learning Is Imparted At A Later Stage This Phase Of Data Collection And Classification Becomes Extremely Vital. Emotional Ques Can Be Obtained Through Various Sources Such As Speech, Images, Text, Biological Sesors Etc. While A Single Source Can Be Used, Multiple Source Almost Always Tend To Impove Efficiency Of Prediction.	This Paper Focuses Primarily On Speech/ Sound Signals As Test Data. Apart From This Using Biological Sensors To Obtain Signals Like ECG And GSR Which Have High Correlations With Emotion Turns Out To Be Extremely Advantageous Majorly Due To Their Non-Maskable Nature.
2.Biological Basis Of Validation	The LIFE Coding Technique Proves To Provide More Valuable And Justifiable Results In A Multitude Of Settings. It Also Provides A Larger Degree Of Emotional Understaning Based On Not Only Verbal But Non-Verbal Ques As Well As Compared To Traditional Valence-Arousal Based Emotional Modeling.	LIFE Coding Technique Provides 27 Content Codes And 10 Affect Codes.This Methodology Is Implemented In A Manner That Replicates Daily Activity And Thus Provides Higher Levels Of Accuracy As Compared To Projection And Classification Of Emotions In Valence Arousal Plane.
3. Pre-Processing	Ensures Extraction Of Valuable Features From The Data And Thereby Elimination Of Unwanted Components Such As Noise. This Can Be Accomplished Through A Variety Of Ways Each Offering Their Own Set Of Advantages.	As Compared To Traditional Methodologies Speech Signals Can Be Regenerated Using Harmonic Models Which Act As A Filter Allowing Only Prosodic And Acoustic Features Of Speech To Pass Through. Apart From This State Models Can Be Implemented With Their Transition Being Goverened By An Attenuation Function. This Provides Promising Results As Indicated Above And Accounts For The Temporal Nature Of Emotions.
4. Learning Model	Data Is Subject To A Model Engineered For Emotional Analysis. A Computational Model Having The Amygdaloid Part And The Orbitofrontal Part Is Used To Receive Inputs. The Amygdala Learns To Predict A System And Never Unlearns A Connection Whereas The Orbitofrontal Part Inhibits The Mismatches Between The Base Systems Predictions And The Actual Received Reinforcer.	Simulations For Testing Features Of Acquisition-Extinction-Reacquisition, Simple Blocking And Conditioned Inhibition Indicate That The Model Contains The Basic Features Of Associative Learning. The Output Of This Model Can Be Used By A Motor Learning System As A Reinforcing Signal For Learning Motor Sequences.

V. Conclusion

This Paper Clearly Outlines The Major Components Involved In The Designing Of An Emotionally Appropriate Artificial Intelligence. Emotions Evennow Remain To Be Highly Convoluted And Their Continuous Nature With No Definite Upper Or Lower Bound Of Intensity Make Them Highly Challenging To Be Designed In A Binary System Of A Computational Model. However, Highly Efficient Methods Have Been Demonstrated Throughout The Course Of This Paper Indicating That Emotions Have To Be Represented In Terms Of Quantifiable Sensory Variables And Efficiency Has Been Highly Increased If These Variables Are Non Maskable [1][3][4][12]. Also Prosodic Nuances Can Be Regenerated Allowing For Higher Degree Of Sensitivity[4][7]. Another Key Property Of Emotions Is Their Time Varying Nature Which Has Been Accounted For By State Models And By Extending Particle Filter Tracking To Sample Transition Models With Higher Contextual Probability[7][10]. This Paper Further Highlights Biologically Inspired Emotional Learning Models And The Amygdaloid-Orbitofrontal System Whose Two Process Model Constructs A Functional Model Of Emotional Processing As Part Of A General Learning System.

An Extension Has Also Been Proposed To Re Generate Cognitive Models As Seen In Highly Sensitive Animals Like Dogs Which May Result In Better Coordinate Emotions With The Temporal, Spatial, Acoustic And Prosodic Components Of Speech[8][9].

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