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A Statistical Data Analytical Model for Metacognitive Reasoning Emotions in Intelligent Systems

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ABSTRACT

Intelligent Systems (IS) have highly increased the autonomy of their decisions, this has been achieved by improving metacognitive skills. The term metacognition in Artificial Intelligence (AI) refers to the capability of IS to monitor and control their own learning processes. Analytical model describes different models used to address the implementation of metacognition in IS. Then, a comparative analysis among the different models of metacognition. As well as, a discussion about the following categories of analysis: types of metacognition, core architectures and metacognition components. IS requiring Human-Robot Interaction (HRI) with better understanding of human emotion. There are few multimodal fusion systems that integrate limited amount of facial expression, speech and gesture analysis.

Keywords: Artificial Intelligence, Metacognition, Metamemory, MetaComprehension, Self-Regulation, Emotion recognition, Human machine interaction, Multimedia, Multimodal.

1. INTRODUCTION

1.1. Metacognition: Overview

"Metacognition" is one of the latest buzz words in educational psychology. We engage in metacognitive activities every day. Metacognition enables us to be successful learners, and has been associated with intelligence. Metacognition refers to higher order thinking which involves active control over the cognitive processes engaged in learning. Activities such as planning how to approach a given learning task, monitoring comprehension, and evaluating progress toward the completion of a task are metacognitive in nature. Because metacognition plays a critical role in successful learning, it is important to study metacognitive activity and development to determine how students can be taught to better apply their cognitive resources through metacognitive control.

"Metacognition" is often simply defined as ***"thinking about thinking".*** In actuality, defining metacognition is not that simple. Although the term has been part of the vocabulary of educational psychologists for the last couple of decades, and the concept for as long as humans have been able to reflect on their cognitive experiences, there is much debate over exactly what metacognition is. One reason for this confusion is the fact that there are several terms currently used to describe the same basic phenomenon (e.g., self-regulation, executive control), or an aspect of that phenomenon (e.g., meta-memory), and these terms are often used interchangeably in the literature and emphasize the role of executive processes in the overseeing and regulation of cognitive processes.

"Metacognition" consists of both *metacognitive knowledge* and *metacognitive experiences or regulation*. Metacognitive knowledge refers to acquired knowledge about cognitive processes, knowledge that can be used to control cognitive processes. It divides metacognitive knowledge into three categories: knowledge of person variables, task variables and strategy variables.

1.1.1. Metacognitive Knowledge

Stated very briefly, knowledge of person variables refers to general knowledge about how human beings learn and process information, as well as individual knowledge of one's own learning processes. For example, you may be aware that your study session will be more productive if you work in the quiet library rather than at home where there are many distractions. Knowledge of task variables includes knowledge about the nature of the task as well as the type of processing demands that it will place upon the individual. For example, you may be aware that it will take more time for you to read and comprehend a science text than it would for you to read and comprehend a novel. Finally, knowledge about strategy variables include knowledge about both cognitive and metacognitive strategies, as well as conditional knowledge about when and where it is appropriate to use such strategies.

1.1.2. Metacognitive Regulation

Metacognitive experiences involve the use of metacognitive strategies or metacognitive regulation. Metacognitive strategies are sequential processes that one uses to control cognitive activities, and to ensure that a cognitive goal (e.g., understanding a text) has been met. These processes help to regulate and oversee learning, and consist of planning and monitoring cognitive activities, as well as checking the outcomes of those activities.

1.2. Emotion: Overview

“Emotions” are based on person’s state of mind and partially regulated by personality, context and conditioning. Emotion is a language for communicating by feelings and it includes approval and disapproval to robotic systems. Interactive emotions are a subclass of human emotion analysis that humans use to interact with each other in close proximity. There are many interactive emotions that a person can express to machine during interaction, such as *happiness, anger, embarrassment, surprise, rage, disappointment, confusion, elation, depression, approval and disapproval*. Interactive emotions are expressed using combination of verbal and nonverbal modes such as facial expressions, speech including silence, gesture including body-posture and body-motion. Single mode may not give the emotion completely, or may be unavailable during emotive interaction.

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For example, the face may be occluded by the hands during sadness when a person is in deep pain or is crying. A person in shock or deep pain may not utter a single word. In the early stages of social robotics, most of the human computer interaction in the service industry will involve brief commands or query by the human, and the robots will play a subordinate role rather than as companion role. Most of the emotion recognition will be limited to the integration of the following

a) Facial expressions

b) The limited amount of speech commands and emotional phrases to provide as an approval, disapproval, encouragement of a robot response or action

c) Gesture analysis of the upper body part involving head, hand, fingers, eyes, and lips.

2. BACKGROUND

2.1. Core Architectures

2.1.1. Theoretical framework for the operation of human memory

A first important contribution in this area was the Theoretical framework for the operation of human memory, which introduced the three principle keys for metacognition: Cognitive processes can be divided into several levels. The Meta level contains a dynamic model of the object level. There are two dominant relationships called control and monitoring. Today, the two-tier architecture is the basis for the architectural design of metacognition in intelligent systems.

The Meta Cognitive Loop (MCL) This is architecture focused on detection of anomalies in learning processes and how to respond to them. MCL presents a general architecture and has three sets of ontologies, which are: ontology for anomaly types, failure ontology for use in assessment, and response ontology for selecting repair types to guide. See Figure

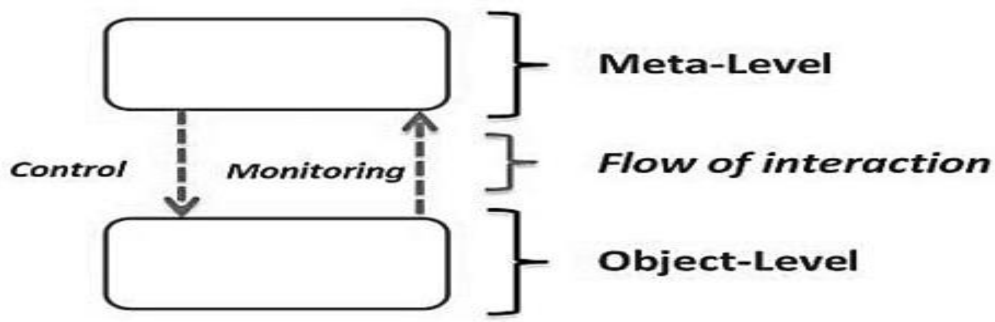

Fig 1: Metacognitive loop

2.1.2. Model for Metareasoning

This model presents a double cycle of reasoning. The first cycle, refers to the traditional conception of cognitive science and AI about the reasoning in IS. Where an intelligent agent receives perceptions of the environment, with which it makes decisions (reasoning), and acts, making changes to the environment. On the other hand, the second cycle of the simple model refers to the perception that the metalevel has about the object level. The metalevel receives information from the object level and makes decisions (metareasoning).

2.1.3. Learning Strategies

The metacognitive architectures are founded on learning strategies. These are: Introspective Learning (IL) , Reinforcement Learning (RL) , Learning by Experience (LE) and Cooperative Learning (CL) .

In computation, *IL* consists of the self-examination or rational self-observation of system reasoning state. *RL* refers to the problem faced by an agent that learns some behavior through trial and error interactions with a dynamic environment. *LE* is a learning technique used in IS, that is based on the solution to new problems by adapting solutions to known problems. *CL* is a learning technique used in MAS, which is based on communications policies and collaborative work.

Fig 2. Learning strategies in metacognition models

2.1.4. Metacognitive Components

With reference to the support of the main components of metacognition: *metamemory, metacomprehension and selfregulation*, the majority of the architectures do not provide support for all three, see Table 1. In relation to metamemory, that *MetaAQUA* has a complex multifaceted memory and reasons about memory events. While, in *MCL* aspects referring to metamemory strategies that can be used to learn from detected failures are left out. Moreover, *MCL* has only basic mechanisms of short-term memory, which in the metalevel are matched with long-term memory. *EMONE* implements a metamemory strategy based on a *CBR* system. *MIDCA* has a memory mechanism that can be accessed from the object level and the metalevel. The rest of the architectures do not present clear support to control and monitor the memory process.

Regarding miscomprehension, MetaAQUA, EMONE and MIDCA are the architectures that offer adequate support. MetaAQUA uses introspection to represent reasoning traces with metaexplanation. EMONE has a strategy known as mental critics that use commonsense narratives to suggest courses of action to deliberate about the circumstances and consequences of those actions.

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In respect to Selfregulation, it can be clearly appreciated that all architectures provide full support for this component of metacognition. In MIDCA the metalevel can act as an executive function in a similar manner to CLARION. CLARION and MCL have better developed metacognitive processes than the rest of the architectures. Note that MetaAQUA, EMONE and MIDCA, are the most complete metacognitive architectures, because they provide support to three main components of metacognition: *metamemory*, *metacomprehension and selfregulation.*

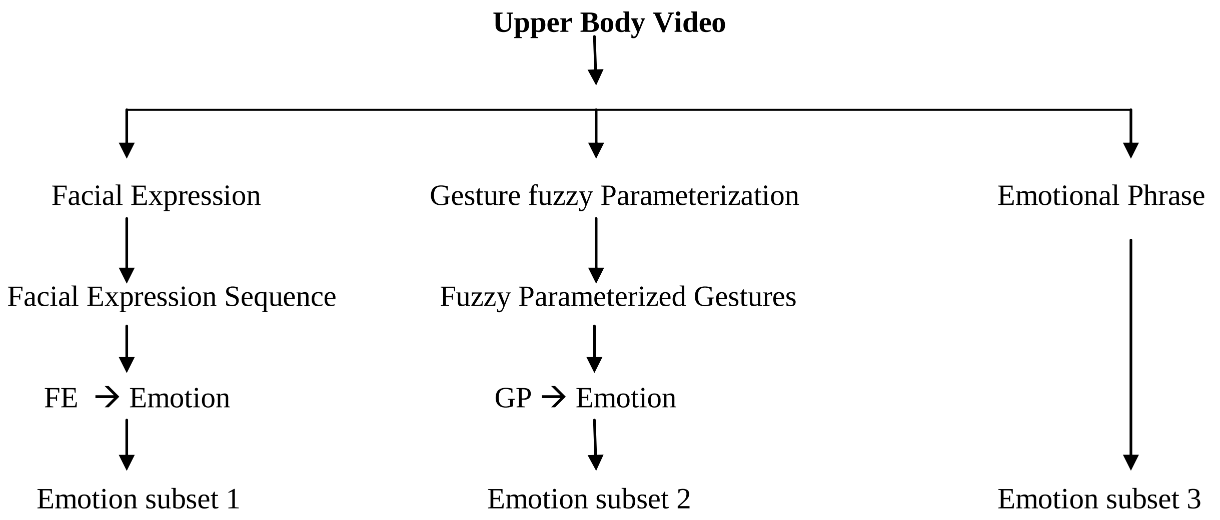
TABLE 1. Support of metacognitive components

MODEL	META-MEMORY	META-COMPREHENSION	SELF-REGULATION
MetaAQUA	Memory Awareness	Story Understanding Meta-XPS(metaexplanation)	Story Understanding
Meta-Cognitive Loop	Basic Mechanism of short-term memory	Basic comprehension of object-level process	Anomoly detection Monitoring and control
Model for metareasoning	----	----	Introspective monitoring
EM-ONE	Memory based on CBR	Mental Critics that use commonsense narrative	Commonsense thinking

3. METHOD

3.1. Multimodal fusion

The model measures different postures and motion intensity and frequency of different emotional gesture patterns. The different postures are: body-posture, head-posture, shoulder-posture, hand-postures, palm-posture, finger-postures and eye-gaze and the various-motions are: head-motion, arm-motions, eye-motions, finger-motions.



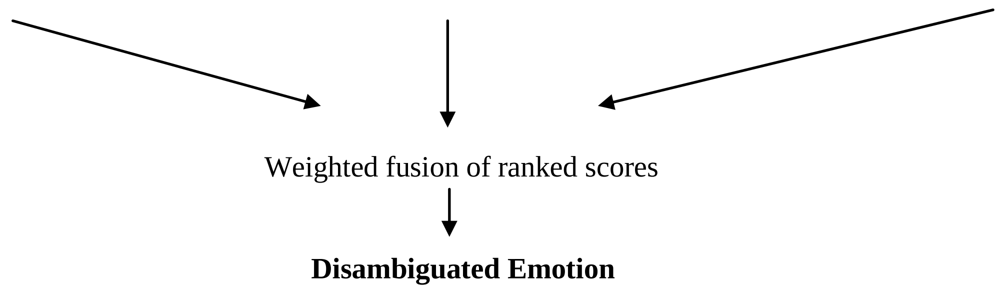


Fig 3. Overall Architecture of Multimodal fusion

3.2. Implementing Emotions

The approach based on decision-level fusion obtained. The performance of the classifier was 91.13%, both for the best probability and for the majority vote plus best probability approaches.

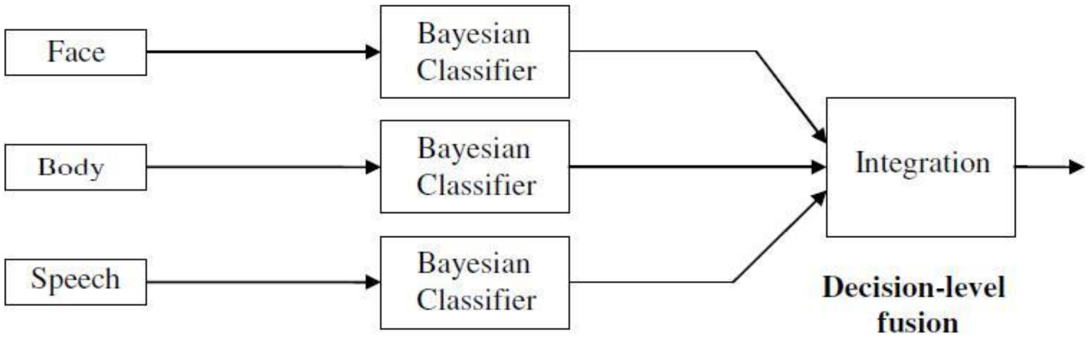


Fig 4.The decision level fusion

Table 2. Shows the performance of the system with decision level integration using the best probability approach. *Ange*r has the emotion recognized with highest accuracy.

TABLE 2. Decision level integration with the best probability approach

Anger	Happy	Sad	Surprise	Disgust	Fear	
98.3	0	0	0	4.3	0	**Anger**
0	**95.4**	0	7.2	0	0	**Happy**
3.1	0	**92.1**	0	2.7	2.2	**Sad**
9.3	10.4	0	**87.5**	2.3	5.8	**Surprise**
7.2	0	4.1	3.3	**90.2**	4.2	**Disgust**
0	0	0	12.2	11.1	**83.3**	**Fear**

4. CONCLUSION AND FUTURE WORKS

In this paper we presented a research article based on four categories of study, there are two predominant types of architectures of metacognition in IS, *centralized* and *decentralized*. The learning strategies present in metacognitive architectures are: Introspective Learning (IL), Reinforcement Learning (RL), Learning by Experience (LE) and Cooperative Learning (CL). Main objective of this work is to use the mathematical framework, in order to impersonate the human thinking process. The model is divided into two sub-processes defined as the generalization related to *human memory* and another one is reasoning related to *human thinking*.

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