A Monitoring System enhanced by means of Situation-Awareness for Cognitive Impaired People

Antonio Coronato
ICAR-CNR
Via Pietro castellino 111
Naples, Italy
antonio.coronato
@na.icar.cnr.it

Giuseppe de Pietro
ICAR-CNR
Via Pietro castellino 111
Naples, Italy
giuseppe.depietro
@na.icar.cnr.it

Giovanni Paragliola
ICAR-CNR
Via Pietro castellino 111
Naples, Italy
giovanni.paragliola
@na.icar.cnr.it

ABSTRACT

The autistic spectrum disorders (ASD) are behaviorally-defined developmental disorders of the immature brain which affects three domains of behavior: sociability and empathy; communication, language and imagination; and mental flexibility and range of interests. Main symptoms include motion disorders and stereotyped behaviors. This paper presents an architecture for recognizing and reporting of anomalous behaviors. The proposed method adopts Situation-Awareness paradigm for the recognition of anomalous behaviors. The architecture enriches the recognizing process with temporal information such as duration and frequency. Results are under validation at the Department of Child Psychiatry at Children' s Hospital Santobono-Pausilipon in Naples.

Keywords

Situation-awareness, Ambient Assisted Living, Human Behavior

1. INTRODUCTION

The autistic spectrum disorders (ASD) are behaviorally- defined developmental disorders of the immature brain. These disorders exhibit by social deficits, communication difficulties, stereotyped or repetitive behaviors and disturb cognitive. Thirty years ago autism was considered a rare childhood disorder most often associated with severe intellectual disabilities, lack of social awareness and the absence of meaningful expressive language [3]. In our work we provide an architecture based on situation awareness (SA) paradigm for monitoring children' s behaviors and reporting information enhanced with temporal data such as duration and frequency. The proposed system is an extension of previews work [8] thereof we will use it as source events for our architecture. Our Solution uses *situation calculus* for modeling intelligent agents able to recognize anomalous behaviors and *Golog* for implementing agents. Results are under validation at the Department of Child Psychiatry at Children' s Hospital Santobono-Pausilipon in Naples

An emerging field of application for human behaviors representation and recognition techniques is the Ambient Intelligence [5]. In [7], we have proposed a process that leads developers to design unambiguous and controllable specification for ambient intelligent, the human behavior is modeled by means of sets of tasks which identify movements, activities and the context. In [10], a system for ambient assisted living is proposed, the human behavior is modeled by means of unsupervised learning algorithms. A behavior is defined as sequence of events or activities, Hidden Markov Model (HMM) is a suitable approach [11]. The major drawback of HMM comes out whenever the context shows unpredictable behaviors, each deviation from normal behaviors needs a human intervention in order to investigate about the cause of the deviation. As long as stereotyped motion disorders are concerned, few approaches based on template matching techniques have been proposed. In [4], authors adopted wearable sensors and machine learning algorithms to identify stereotyped motion disorders of children with autism. They have focused on two motion disorders: hand flapping and body rocking. In [6], we have proposed a situation-aware system able to detect abnormal behaviors of patients with Alzheimer, we have used an approach based on intelligent agents, to detect and recognize anomalous situation. Our proposal gets the sequence of events generated by [8], these events are processed by intelligent agents for obtaining temporal information useful for the clinicians and reducing misclassifications.

The paper is structured as follow. Section 2 presents Situation-Awareness paradigm. Section 3 describes the proposed approach. Section 4 shows the results and concludes the paper dealing with potentials of the proposed approach.

2. SITUATION AWARENESS

Situation awareness is the perception of environmental elements obtained by means of multi-levels semantic approach. In [13], authors define two macro levels: *Primary context* and *Secondary Context*. *Primary context* is the full set of data caught by real and virtual sensors; *Secondary context* concerns with information inferred and/or derived from several data streams (primary contexts) and an important kind of secondary context is activities performed within the environment. Situation-awareness includes rich temporal and other structural aspects, like: *time-of-day*, a situation may

BODYNETS 2013, September 30-October 02, Boston, United States

DOI 10.4108/icst.bodynets.2013.253551

only happen at a particular time of the day; *duration*, it may only last a certain length of time; *frequency*, it may only happen a certain number of times per day, and *sequence*, different situations may occur in a certain sequence. The situation model has been described by using Situation Calculus (SC).

Situation calculus is a logical language for representing dynamic word. It was introduced by McCarthy [9]. Basic concepts of situation calculus are *situations*, *actions*, *fluents*. *Actions* define all possible actions performable in the domain, for example *pickUp(Object,t)* denotes the action of picking up an object at time t. *Fluents* are situation-dependent functions used to describe effects of actions. There are two kinds of them: relational fluent and functional fluent. The first one have only two values: true or false, while the latter can take a range of values; for example *isPlaceOn(Knife,Table,S)* might be a relational fluent that denotes the situation S whereby the *Knife* is on the *table*. According to McCarthy, a situation is the complete state of the universe at an instance of time. But for Reiter [12], a situation is the same as its history which is the finite sequence of actions that has been performed since *S0*, where *S0* is the initial situation; an example *do(putOn(book,table),S0)* denotes the new situation *S* resulting from putting the book on the table in the initial situation *S0*. Whatever the interpretation, the unique feature of the situation calculus is that situations are first-order objects that can be quantified. This is what makes the situation calculus a powerful formalism for representing change. A basic action theory is a set of axioms including the initial world axioms, unique names axioms, actions precondition, and successor state axioms. *Actions precondition*, action could be not executable in a given situation, these axioms describe the conditions under an action is performable. *Poss(a,S)*, where *a* is an action, *S* is the current situation and *Poss* is a binary predicate that denotes executable of actions. *Success state axioms* (SSA) describes a dynamically changing world. A generic form of SSA is :

$$F(\vec{x}, do(a,S)) \equiv \gamma_F^+(\vec{x}, a, S) \vee (F(\vec{x}, S) \wedge \neg\gamma_F^-(\vec{x}, a, S)) \quad (1)$$

where γ_F^+ ($\vec{x}$,a,S) is a first-order formula- with free variables among x, a, and S -that makes the Fs truth value changing to true. Analogously, γ_F^-($\vec{x}$,a,S) is a first-order formula that makes the Fs truth value changing to false. *Unique names axioms* state all actions have a unique name. A special predicate is *do(a,S)* that indicates the situation resulting from the execution of the action *a* in situation *S*. *Initial world axioms* define a set of first order sentences that list fluents's truth value in the initial situation and entities's properties.

3. PROPOSED APPROACH

In [8], authors propose an approach for the detection of stereotyped motion disorders of patients with ASD. Motion disorders are classified in four anomalous gestures: *Hand hitting against the Ear, Arm Flapping , Hand Rotation Up, Hand Rotation Down*. Each kind of gesture is modeled with an opportune event that notices an anomalous gesture is involved: *Hand hitting against the Ear* $\Rightarrow$ **HE**;
Arm Flapping $\Rightarrow$ **HF**; *Hand Rotation Up* $\Rightarrow$ **HRU**;
Hand Rotation Down $\Rightarrow$ **HRD**. The classification is performed by means of Neural Network algorithms [2]; we have chose to adopt Neural Network fallowing on from a comparison amongst Neural Networks, Naive Bayes and Bayesian Networks. Experimental results have highlighted better classification performances for the neural network, whereas other classifier show faster training, for more information about classification method please reference to [8]. Unfortunately, we have experimentally verified the occurrence of different misclassifications errors related to the sequence of events during the detection process. The most frequent misclassifications errors are:

- spurious misclassifications, that are false positives related to a one singular temporal frame misclassified as abnormal status when the gesture is normal;
- misclassifications due to short pauses in the motion of the patient.

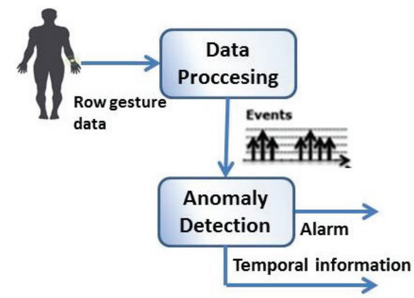

Figure 1: Data Workflow

In case of a short pause during the abnormal gesture, from a clinical point of view, it is related to the same event instead of two different ones. In order to remove these problems we have developed intelligent agents in *Prolog*, a general purpose logic programming language for *Situation Calculus*. Agents also provide temporal information about occurrence of anomalous gestures such as duration and frequency. Figure 1 describes the data work-flow. The Data Processing component (DPC) executes a data processing from patient's moving data to out-coming anomalous events. DPC is composed by three main sub-tasks: 1) Collect primary context data from patient's wrist by means of accelerometers, 2) extract statistic features from primary context data, 3) use these statistical features for recognizing and generating anomalous events. More details about this process are provided in [8]. The anomaly detector is the component that embodies the intelligent logic for reducing misclassifications and providing temporal information. From now on, we focus only on intelligent agents.

3.1 Intelligent Agents

In order to remove misclassifications errors described in the previous section we adopt Situation Calculus. *Situation Calculus* (SC) is a first order logic adopted for developing agents. The intelligent prolog agents implement the following SC specification. Axiom 2 defines actions performable in the environments, for the sake of brevity we post only a sub-set of them.
$\mathbf{HE(t)}, \mathbf{HRU(t)}, \mathbf{AF(t)}, \mathbf{HRD(t)}$ are events used for modeling anomalous gestures, they are defined as *Exogenous actions* that can being execute only by the patient.
$\mathbf{NORM(t)}$ is an *exogenous action* that represents a non-anomalous gesture.

$\mathbf{Reset(t)}, \mathbf{markStartTime(t)}$ are named *Endogenous actions* and they exclusively can being performable by agents for technical reason (e.g. markStartTime(t) marks the starting time of the anomaly).

$$a \in \{\mathbf{HE(t)}, \mathbf{HRU(t)}, \mathbf{AF(t)}, \mathbf{HRD(t)}, \mathbf{NORM(t)}, \mathbf{reset(t)}, \mathbf{markStartTime(t)}\} \quad (2)$$

Axiom 3 is a relational fluent that triggers whenever a spurious misclassifications is detected. $T_{Currence}$ is the arrival time of the current occurrence event, T_{Last} is the arrival time of the previous event, $T_{WaitSucc}$ is a waiting time for the next event; $\Delta_1 and \Delta_2$ are two temporal thresholds, they have been set on the advice of clinicians. *isSpurius* changes its truth value whenever the difference $|T_{current} - T_{Last}|$ not exceed Δ_1 and the waiting time for the successor events limits over Δ_2. The drawback of this solution is an insertion of a temporal delay in the reasoning process same as $T_{WaitSucc}$ parameter. The endogenous actions *reset* sets fluent's truth value to false.

$$\begin{aligned} &\mathbf{isSpurius(do(A, S))} \quad (3)\\ &\equiv \{A = HE(t) \vee A = AF(t) \vee A = HRU(t) \vee A = HRD(t) \wedge \\ &T_{current} = time(A) \wedge |T_{current} - T_{last}| < \Delta_1 \wedge \\ &|T_{WaitSucc}| > \Delta_2 \\ &isSpurius(S) \wedge (A = reset)\} \end{aligned}$$

Axiom 4 is a relational fluent and denotes the situation produced when an anomalous motion is recognized. it changes its truth values whenever an event such as HRU(t) is detected and it is not a spurious misclassifications. Fluent becames false when a non-anomalous gesture is recognized and the event *NORM(t)* is generated.

$$\begin{aligned} &\mathbf{isAnomaly(do(A, S))} \quad (4)\\ &\equiv \{A = HE(t) \vee A = AF(t) \vee A = HRU(t) \vee A = HRD(t)\} \\ &\neg isSpurius(S) \vee \\ &isAnomaly(S) \wedge \neg\{A = NORM(t)\} \end{aligned}$$

Axiom 5 reduces misclassifications problems due to a short pause in the sequence of events. Once an anomaly is recognized the fluents *isAnomaly* triggers; if the difference $|T_{Last} - T_{Current}|$ not exceed a temporal thresholds Δ then *shortAnomaly* will change its truth value.

$$\begin{aligned} &\mathbf{shortAnomaly(do(A, S))} \equiv \quad (5)\\ &\equiv \{A = HE(t) \vee A = AF(t) \vee A = HRU(t) \vee A = HRD(t) \wedge \\ &isAnomaly(S) \wedge \\ &T_{Current} = time(A) \wedge |T_{Last} - T_{Current}| < \Delta \ \vee \\ &shortAnomaly(S) \wedge (A = reset)\} \end{aligned}$$

Axioms(6, 7) are functional fluents which provide temporal information as the period of day within gesture is recognized.

$$\begin{aligned} &\mathbf{anomalyPeriodOfTime(Period, do(A, S))} \equiv \\ &\{A = HRU(t) \vee A = HRD(t) \vee A = HE(t) \vee A = AF(t)\} \wedge \quad (6)\\ &Period \in periodOfDay(Ts, Tf) \\ &\wedge \neg\{(anomalyClassifier(S)) = Normal\} \end{aligned}$$

$$\begin{aligned} &\mathbf{periodOfDay(tS, tF)} \equiv \quad (7)\\ &\{(P = Morning \wedge tS = 6:00 \wedge tF = 12:00) \\ &\vee (P = Afternoon \wedge tS = 12:01 \wedge tF = 18:00) \\ &\vee (P = Evening \wedge tS = 18:01 \wedge tF = 24:00)\} \end{aligned}$$

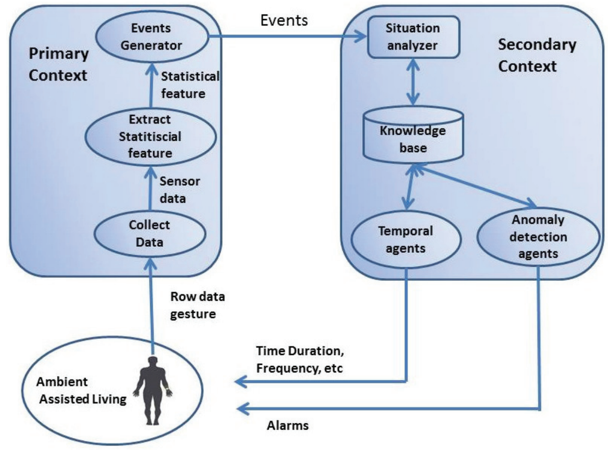

Figure 2: Architecture

Axiom 8 is also a functional fluent that provides the duration time of the anomaly.

$$\begin{aligned} &\mathbf{anomalyDuration(Duration, do(A, S))} \quad (8)\\ &\equiv A = markStartTime \wedge \\ &isAnomaly(S) \wedge T_{StartAnomaly} = time(A) \vee \\ &anomalyDuration(Duration, S) \wedge \neg\{A = checkDuration(t) \\ &\neg shortAnimaly(S) \wedge T_{Finish} = time(A) \\ &|T_{Start} - T_{Finish}| = Duration\} \end{aligned}$$

3.2 Software Architecture

The prototype architecture that we are developing for the monitoring of cognitive impaired is shown in Figure 2. The system consists of two macro components which embody *Primary context* and *Secondary context*. Primary context executes a data processing since collecting row data gesture to generating events. In order to acquire motion data, we apply an accelerometer to the patient' s wrist. The accelerometers is the eZ430-Chronos. It includes an integrated pressure sensor and a 3D-axis accelerometer for motion sensitive control. Signals are pre-processed in order to extract statistical features useful for generating events. In order to identify motion disorders and generate opportune events we adopt Neural Networks algorithms. We adopts this approach because it is very spread in literature, [4] is an example of that. For more details about primary component refer to [8], please. The *Secondary context Component* fulfills our approach. It is composed of the situation analyzer and intelligent agents. *Situation Analyzer* is the one that receives events from primary context components and updates the current situation as agents's truth value. The *knowledge base*, *Temporal agents*, *Anomaly detection agents* are developed by means of *Golog*, the prolog interpreter for Situation Calculus. The Prolog engine used for executing and reasoning agents is ECLiPSe [1]. ECLiPSe is a temporal reasoner for the development and deployment of constraint programming logic applications. The *knowledge base* stores *Initial World Axioms* and tracks the current situation *S*. *Anomaly detection agents* monitor patient's behaviors and generate alarms whenever an anomalous gesture is recognized. They reduce misclassifications problems as defined by axioms 3, 4, 5. The *Temporal Agents* provide information such as time duration and frequency for enriching clinical data reports. They monitor values of fluents dedicated to temporal information (axioms 6, 7, 8). Figure 3 shows an use case scenario. A sequence of HF events are generated by the Neural network, this means that an anomalous gesture is involving. The short pause in the middle of the sequence mistakes the Neural network that recognizes two distinct anomalous gestures G1 and G2. This kind of misclassifications is removed by submitting the sequence to prolog agents. The short pause Δ_t is recognized shorter then temporal thresholds Δ so it is ignored. The *isAnomaly* agent detects only one gesture, *anomalyDuration* returns the duration time (Δ_T=15 seconds), and *periodOfDay* returns the period of day within gesture happens.

4. RESULTS AND CONCLUSIONS

A prototype of such a system is deployed to Santobono-Pausillipon Children Hospital, the software is installed on intel i7-3770 3,4GHz with 8GB RAM, 1600Hz. The accelerometer eZ430-Chronos is placed on patient's wrist for whole examination time, all device are located inside a room 6x5m whose dimensions are compliant to working range of the sensor. Figure 4, reports the results of the monitoring in the hospital of four different patients in four daily observations. We have verified for the on-line ANN Classifier performance that the accuracy is near to 92% worse then off-line ANN Classifier performance over 98%. This result has been obtained by the ANN Classifier matching real patients gestures again with patterns of motion disorders imitate by clinicians for training the Neural network. For more information about results of the ANN Classifier please reference to [8]. The intelligent prolog agents have identified two motion disorders of type HE for one patient. Other patients have not shown any motion disorders during the observation. Disorders of type HE have been the result of a sequence of fifteen events classified as HE by the artificial neural network. The disorders held on for fifteen seconds and both have been detected at Morning. It is finally useful to note that the neural network had detected one spurious event classified as HRD for the first patient, such misclassifications has been purged by agents. In this paper we have presented an architecture based on situation-awareness for reducing misclassifications of stereotyped motion disorders in children with Autism Spectrum Disorders. Actually we are still collecting real data from system in order to proof the soundness of our approach. Preliminary laboratory results have encouraged the adoption of such approach. However, several improvement are possible in future work. We would like to considered the problem related to delay generated by the agent for recognizing spurious events, we also are investigating about new specification for the agents.

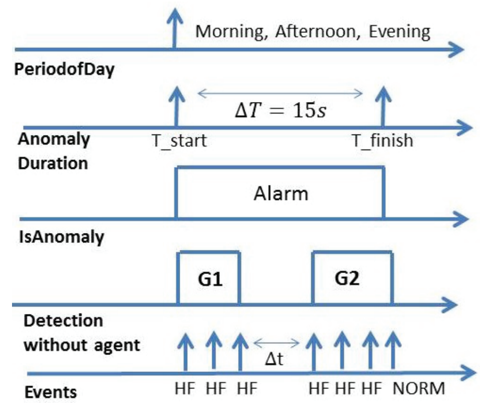

Figure 3: User Case Scenario

	Neural Network Classification	Agents Classification							
		Day		Morning		Afternoon		Evening	
	N°	N°	Δ	N°	Δ	N°	Δ	N°	Δ
HE	15	2	15s	2	15s	0	0	0	0
HRU	0	0	0	0	0	0	0	0	0
HRD	1	0	0	0	0	0	0	0	0
HF	0	0	0	0	0	0	0	0	0

Figure 4: Results

5. REFERENCES

[1] Eclipse prolog.

[2] Introduction to artificial neural networks. In *Electronic Technology Directions to the Year 2000, 1995. Proceedings.*, pages 36–62, 1995.

[3] A Parent's Guide to Autism Spectrum Disorder, 2011.

[4] F. Albinali, M. S. Goodwin, and S. S. Intille. Detecting stereotypical motor movements in the classroom using accelerometry and pattern recognition algorithms. *Pervasive and Mobile Computing*, pages 103–114, 2012.

[5] D. J. Cook, J. C. Augusto, and V. R. Jakkula. Review: Ambient intelligence: Technologies, applications, and opportunities. *Pervasive Mob. Comput.*, 5(4):277–298, Aug. 2009.

[6] A. Coronato and G. De Pietro. Situation awareness in applications of ambient assisted living for cognitive impaired people. *Mobile Networks and Applications*, pages 1–10, 2012.

[7] A. Coronato and G. D. Pietro. Formal design of ambient intelligence applications. *Computer*, 43(12):60–68, 2010.

[8] A. Coronato and G. D. Pietro. Detection of motion disorders of patients with autism spectrum disorders. In *IWAAL*, pages 415–422, 2012.

[9] J. McCarthy. Situations, actions, and causal laws. Technical Report Memo 2, Stanford Artificial Intelligence Project, Stanford University, 1963.

[10] D. Monekosso and P. Remagnino. Behavior analysis for assisted living. *IEEE Transactions on Automation Science and Engineering*, 7(4):879 –886, oct. 2010.

[11] L. Rabiner and B.-H. Juang. An introduction to Midden Markov Models. *IEEE ASSP Magazine*, 3(1):4–16, 1986.

[12] R. Reiter. *Knowledge in Action: Logical Foundations for Specifying and Implementing Dynamical Systems.* The MIT Press, Massachusetts, MA, 2001.

[13] J. Ye, S. Dobson, and S. McKeever. Situation identification techniques in pervasive computing: A review. *Pervasive and Mobile Computing*, In Press, Corrected Proof:–, 2011.