

A Behavioral Action Sequences Process Design

Moataz Kilany^{1,*}, Aboul Ella Hassanien^{2,3,*}, Amr Badr²

¹Minia University, Faculty of Computers and Information, El-Minia, Egypt

²Faculty of Computers and Information, Cairo University, Egypt.

³Faculty of Computers and Information, Beni Suef University, Egypt

*Scientific Research Group in Egypt (SRGE)

<http://www.egyptscience.net>

Abstract. Modeling human actions in a format that is suitable for computer systems to understand is a target for behavior analysis systems. This work introduces a high level design for a behavioral analysis system based on action sequences. The design is introduced in terms of process modeling. System processes are presented in terms of a set of data flow diagrams (also known as DFDs) of multi levels. They represent the decomposition of all processing components required in such system and the data flows among them. The system is designed to receive structured information for human behaviors and actions and produce insights, predictions and classifications for personal and behavioral characteristics. Proposed process decomposition is introduced as a core step towards design and implementation of a behavior analyzer system.

This work also introduces an approach to model the contextual factors affecting personal activities. This should lead to a more precise behavioral models that can capture activities as well as considering contextual factors such as the surrounding physical environment, person committing the activity, surrounding culture, social, and religious norms. The targeted accuracy of modeling is meant by the precise evaluation of personal activities after taking all mentioned factors into account.

Keywords: Human Behavior Analysis, Prediction, Process Modeling, Data Flow Diagrams.

1 INTRODUCTION

Modern computer systems rely on advanced human interfaces designed to understand behavioral patterns and produce natural and intelligent response accordingly, human-machine interaction is a vital trend in this field [1]. Human behavior analysis system aims to make human interactions effective, employing a behavioral model that preserves data structures for actions information and functions that perform behavioral analysis. The targeted output of such analysis here is to produce generic insights about action sequence patterns after application of psychological theories and logic relations among behavioral factors and modifiers. By generic we mean the level of extensibility and abstraction, where the core data elements are designed to abstract human behaviors of any type

in any context, with defined rules that can be extended at any point of system lifetime. This in addition to a prediction component to foresee future behavioral sequences of actions and of human affects such as personal mood, attitude and emotions. A number of modeling ideas appeared in research efforts upon which we built our modeling approach. [2], [3] discussed ideas for the representation of human actions.

Process modeling is an important step in system analysis and design. This work introduces a decomposition of all required logical processes inside the targeted behavior analysis system in terms of a set of data flow diagrams [4]. We start from context diagram through level one of decomposition. The proposed process model is a step towards design and implementation of a human behavior analysis system.

There exist many modeling efforts in former research such as, the identification of personal intentions [5], tracking human actions during driving [6]. All former efforts focused on a given context of actions and isolated many environmental variables. Such as limiting the location, the time and other important factors. A number of researchers focused on defining context-aware systems as for Cosimo Palmisano et.al [10], where context is defined as the customer intent of purchase in an e-commerce application. In [11], the location of a person, surrounding people identities and objects were considered for contextual analysis. Others relied on timing, season, and temperature [12].

This work is organized as follows; Section (2) Discusses the overview of system design, input, and output, section (3) Shows the higher level of composition for the system, section (4) and (5) show level 1 and level 2 of decomposition respectively, section (6) discusses a rule-based approach for representing the context of human actions.

2 System Context

The following paragraphs introduce an overview of system in terms of input, output and processes.

Input Set:

- **Actor Information**, A history about targeted persons for analysis purposes such as a list of action sequences, contexts, locations, and other data elements.
- **Action Information**, Action is a main data element in proposed system, composed of three factors; a descriptive verb, a target of action, and an actor along with a set of temporal modifiers. This abstract definition enables the system to deal with any action whether physical, oral or mental.
- **Personality Classification**, Represents a set of ten factors employed by the big five aspect scales of the big five personality traits theory [13], each represented by a quantifiable variable. Those factors are neuroticism, agreeableness, conscientiousness, orderliness and extraversion. The five traits are decomposed into ten aspect scales which are targeted here.

- **Personal Attitude, Personal Rules, Location Rules**, Action context is also a major element in the system data model. It is the surrounding controlling factors that affect evaluation of a given behavior, a behavior can be treated as aggressive or abnormal in some environments, while not in others [14]. The context of a given action is represented in terms of a set of rules that, for each human action, define information for action and environment information, and a directed value (positive/negative) defining how much this action is tolerated or accepted in the given environment. A context can be a person, physical location, logical location, culture or a religion [15], [16]. A set of rules each incorporates a positive value defining personal attitude towards the action target.
- **Location Information**, A set of items defining location of action either contextual location (work, home, street or others) or a physical location addressing the country, state, town, continent and coordinates. Such locations are assigned contextual rules to capture location-based context as discussed in previous section.
- **Behavior Classification**, A classification of behavior in terms of personal affects such as aggression, anger, enthusiasm and other.
- **Action Motivation**, A classification for action based on motivation. This work applied Alderfer's theory of motivation [17] which decomposes motivations into three factors; existence, relatedness and growth motivations.

Output Set: Most output data elements are previously defined in section 2 and will be briefed here.

- **Personal Attitude (Rule Set)**, An updated attitude value.
- **Personality Classification**, An updated personality classification.
- **Behavior Classification**, An updated behavior classification.
- **Action Motivation**, An updated value for motivation.
- **Personal Mood**, An inference evaluating personal mood in terms of a directed weighted value. This inference depends on a set of logic rules that map a range of sequences of actions to an evaluation for personal mood.
- **Predicted Action Sequences**, A predicted action sequences set, based on pattern matching algorithms applied on a history of action sequences.
- **Predicted Mood**, A predicted mood based on the predicted sequences of actions and a set of inference rules.
- **Predicted Attitude**, A prediction for personal attitude towards an object based on pattern matching applied on patterns of actions (action sequences).

3 Level Zero Data Flow Diagram

This section shows the decomposition of internal processes along with data flows employing a level zero data flow diagram presented in Fig. 1 which identifies a set of six processes and 5 data stores responsible for data storage.

Internal Processes:

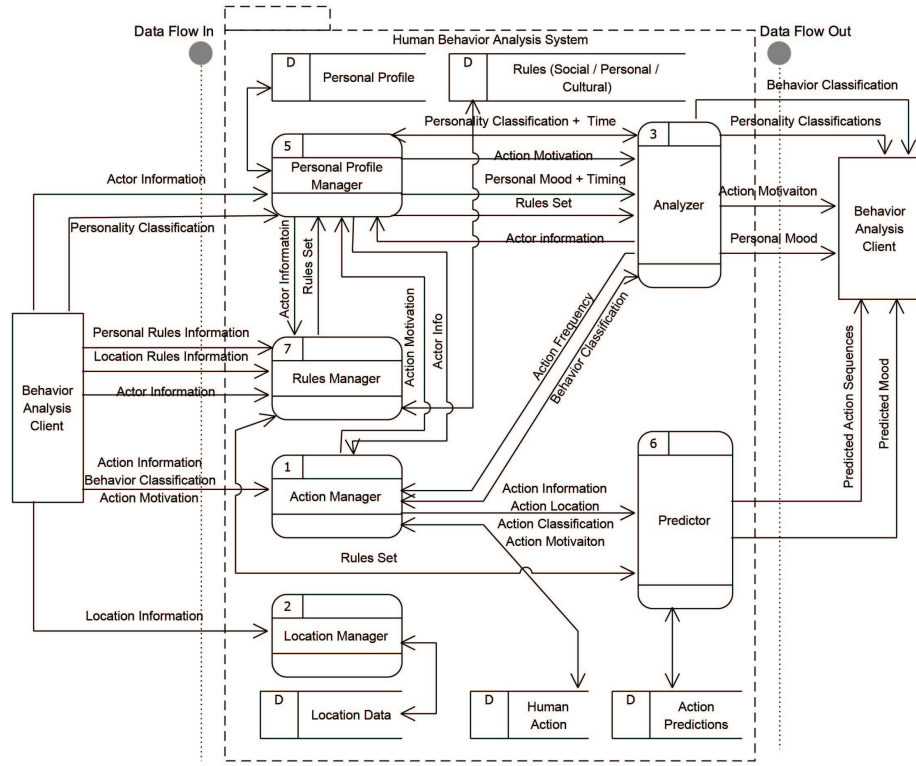


Figure 1: Level-0 DFD Diagram for Human Behavior Analysis System

- **Action manager**, Responsible for actions information storage, retrieval and action sequences similarity check and pattern matching.
- **Location Manager**, Responsible for location information management discussed in section 2.
- **Analyzer**, Incorporates logic and mathematical rules based on psychological theories and logic insights to analyze patterns of actions and make inferences about actions.
- **Profile Manager**, Manages action actors information as shown in section 2.
- **Predictor**, Responsible for prediction logic, receives sequences of actions and applies a set of pattern matching algorithms to predict future sequences.
- **Rules Manager**, Responsible for storage and retrieval of rules that are the basis of actions context and personal attitude as discussed in section 2.

4 Level One Data Flow Diagram

Presents a decomposition of level zero DFD. Most important decompositions discussed here are the analyzer and action predictor processes appearing in Fig. 2.

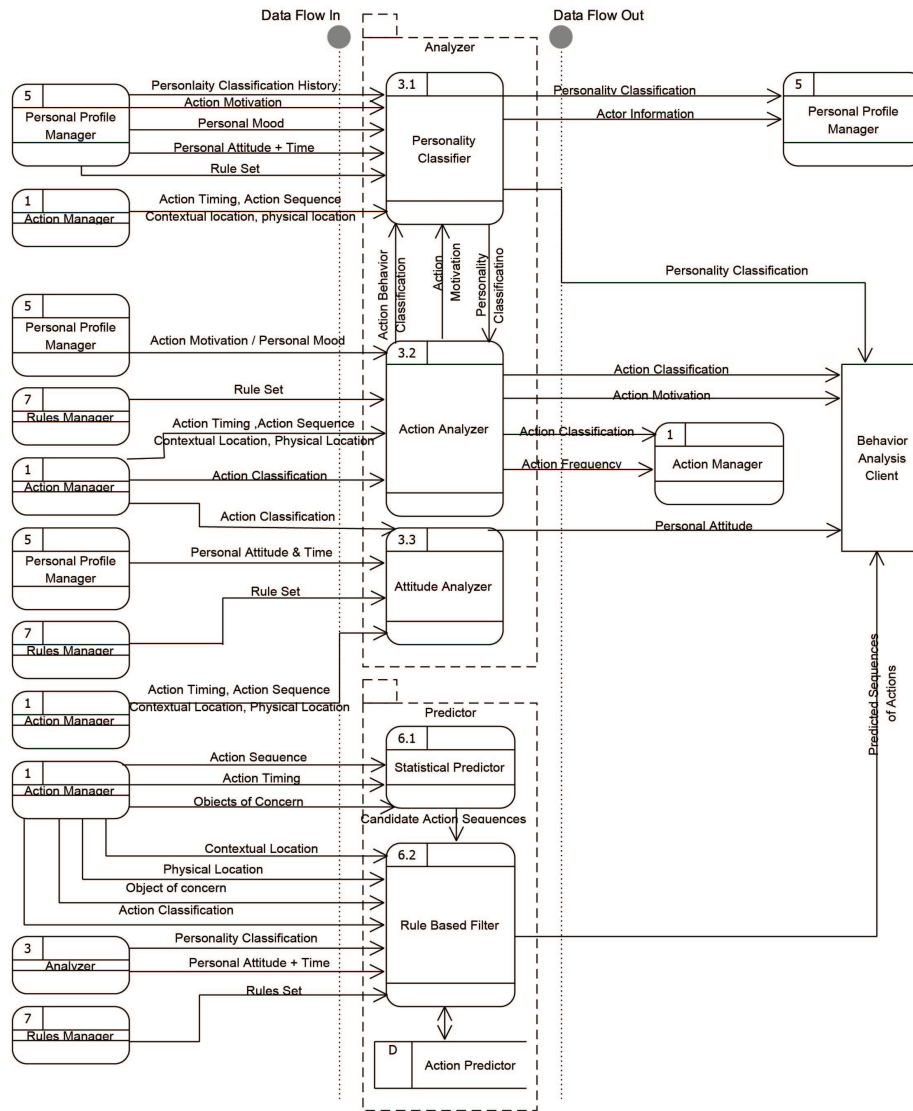


Figure 2: Level 1 DFD Diagram for Human Behavior Analysis System

Data Elements:

- **Action sequences**, A set of predicted action sequences based on statistical analysis for action history.
- **Object of concern**, A real world object that is a target of a given action. Can be a real world item, a person or another action.

- **The Action Predictor Process**, The prediction component, composed of a statistical predictor and a rule based filter.
- **Statistical Predictor**, Makes use of action sequences history to predict the most probable sequences of actions, employs a set of pattern matching procedures applied on a large data base of action sequences [18].
- **Rule Based Filter**, Helps the statistical predictor narrowing expected results based on context. Also makes suggestions about future actions based on a set of inference rules that maps a combination of personality classifications, attitudes, and locations into expected sequences. Research in [19] applied a similar approach.

Level 1 Processes: Generates inferences about behavior classification, personality classification, action motivation and personal mood. It employs three processes; Personality classifier, action analyzer and attitude analyzer.

- **Personality Classifier** Depends on a set of inference rules to identify the five personality aspect scales by combining the time factor along with personal mood, identified action motivations, action sequences and their frequencies.
- **Action Analyzer** Identifies for a given action, a classification, motivation and action frequencies.
- **Attitude Analyzer** Makes inferences on personal attitude based on classifications for the given action, personal attitude history and based on the history of action sequences and their context.

5 Level Two Data Flow Diagram

The next level of decomposition focuses on process 3.1 and 3.2, the personality classifier and action analyzer respectively. both processes are decomposed into seven functions presented in the following sections.

The Action Analyzer Process: Action analyzer employs three processes; The frequency calculator, motivation identifier and action classifier.

- **Frequency Calculator** Responsible for matching new sequences of actions with action history based on a given affinity value to calculate how frequent a given single action or a sequence of actions is recurring on a given time unit. [20] and [18], introduced valuable ideas for defining behaviors and how to formally define and measure behavior frequency. Affinity measurement between action sequences is applied in all core processes such as frequency calculator, statistical predictor, and other action analysis elements. Multiple sequences of actions can lead to the same behavior. Here, we apply the Needleman-Wunsch algorithm that is being applied in many distance measurement applications [21]. Algorithm. 1 employs the Needleman-Wunsch algorithm to measure distance or affinity between two given sequences of actions, where (**d**) is an initial value for first row / column of matrix. The algorithm builds a two dimensional

scoring matrix (D) with dimensions ($\mathbf{N} * \mathbf{M}$) where N, M are here the lengths of both action sequences applying the following rule:

$$D(i, j) = \max_{\substack{0 \leq i \leq N \\ 0 \leq j \leq M}} \begin{cases} D((i-1), (j-1)) + s(x_i, y_i) \\ D(i-1, j) + g \\ D(i, j-1) + g \end{cases} \quad (1)$$

where ($s(\mathbf{x}_i, \mathbf{y}_i)$) finds the equality of two single actions ($\mathbf{x}_i, \mathbf{y}_i$). Once the scoring matrix is calculated, the affinity among both sequences of actions ($\mathbf{A}_1, \mathbf{A}_2$) is identified by the value of cell $\mathbf{D}(\mathbf{N}, \mathbf{M})$ in scoring matrix.

Algorithm 1 Needleman-Wunsch algorithm - action sequences similarity

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1: Input: Action sequence 1 ( $A_1$ ) sequence 2 ( $A_2$ )
2: Output: A Scoring Matrix  $D$ 
3: for  $i \leftarrow 0$  to  $Length(A_1)$  do                                      $\triangleright$  Initialize scoring matrix
4:    $D(i, 0) \leftarrow (d * i)$ 
5: end for
6: for  $j \leftarrow 0$  to  $Length(A_2)$  do
7:    $D(0, j) \leftarrow (d * j)$ 
8: end for
9: for  $i \leftarrow 0$  to  $Length(A_1)$  do                                      $\triangleright$  Insertions - Deletions calculation Eq. (1)
10:  for  $j \leftarrow 0$  to  $Length(A_2)$  do
11:    Match  $\leftarrow D(i-1, j-1) + S(A_1(i), A_2(j))$ 
12:    Delete  $\leftarrow D(i-1, j) + d$ 
13:    Insert  $\leftarrow D(i, j-1) + d$ 
14:     $D(i, j) \leftarrow \max(\text{Match}, \text{Insert}, \text{Delete})$ 
15:  end for
16: end for

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- **Motivation Identifier:** Combining patterns of action sequences with their contexts (in terms of rules as discussed before) to infer motivational factors about such sequences. [22] discusses how to computationally represent human motivations and actions. This research employs Alderfer’s theory of motivation to similarly represent motivations in a computational manner.
- **Action Classifier:** Makes classification of actions on the basis of their frequencies and a comparison of action rule set with the context rule set to identify specific classifications such as aggressive, angry, or normal actions.

The Personality Classifier Process:

Produces inferences about personality traits based on a number of different approaches, each one is applied by an internal process. The results of classifications are finally merged to produce an enhanced classification list. This employs four processes; (1) The rule set analyzer, (2) action history classification analyzer, (3) psychological affect analyzer, and (4) a personality classifier which merges all results and produces the final inferences.

Rule Set Analyzer: Applies a set of inference rules on the contextual rules of a given actor. Such contextual rules are to give indications about his personality traits.

Action History Classification Analyzer: Makes inferences of personality traits based on the history of action sequences and their classifications.

Psychological Affect Analyzer: Makes analysis based on the history of recorded motivations, personal mood, and attitude for a given actor.

Personality Classifier: Makes a merging process to the supplied lists of personality classifications and produce a refined list of the big five aspect scales.

6 Rule-Based Context Representation

As discussed before, a set of rules can define action tolerance with respect to some context to reflect a very high level of granularity in representing contextual effects. There are many examples of contexts; a person, location, time, contextual location, culture, religion, social group, human crowds and others.

6.1 Core Entities

In order to represent human actions in terms of a set of rules, we need to begin by defining the required data entities to be used by such rules later.

- **Action Sequence** Represents a sequence of human activities and expressed by the following tuple.

$$a = \{(\{\hat{a}_1, \hat{a}_2, \dots, \hat{a}_n\}, pr, l, c, pi, pm, o, v)\} \quad (2)$$

Where, $(\hat{\mathbf{a}}_1)$ through $\hat{\mathbf{a}}_n$ is a list of action characteristics. (\mathbf{pr}) , internal action sequence. Each action consists of an inner sequence of more trivial actions. (\mathbf{l}) , a list of action characteristics. (\mathbf{c}) , the context of action. (\mathbf{pi}) , personal profile information. (\mathbf{v}) , action verb. (\mathbf{o}) , the targeted object of the given action.

- **Action Context** Any entity that can change action evaluation such as the time of action, actor, physical location, contextual location and the set of social, cultural and religious factors.
- **Action Evaluation** Visualized in Figure 4. Action is evaluated in terms of how much it is accepted in a given context and with a given criteria and represented by a directed value (positive / negative) identifying the acceptance of action along with the strength of such acceptance.
- **Activity Environmental Rules** A personal action is controlled and evaluated on the basis of surrounding environment. Many research efforts discussed the effects of environment on human behavior as in [23] Here, the environment can be the person committing the action, location, time, or the set of social and cultural rules controlling action. A contextual rule is represented by a tuple of four elements; The action being evaluated (denoted by (\mathbf{a})), The context of action (denoted by (\mathbf{c})), and action tolerance value (denoted by (\mathbf{t})) that identifies the tolerance of action in the given environment using a directed value. Rule definition appears in 3.

$$r = (a, c, t) \quad (3)$$

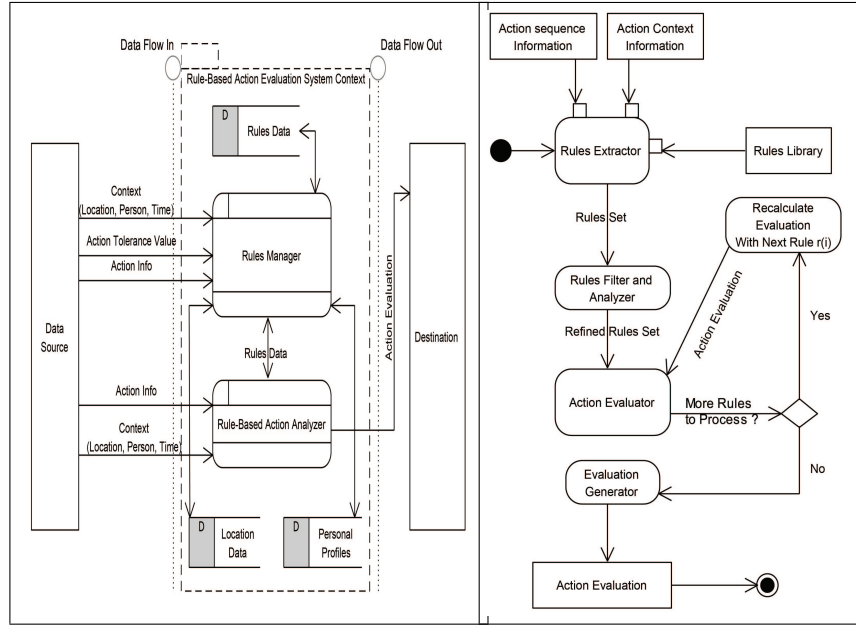


Figure 3: Rule-Based Action Evaluation System Context

Figure 4: Rule-Based Action Evaluator component Context

7 Conclusion and Future Work

This work presented a design approach using a process model of a human behavior analysis system. The model presented a decomposition of effective internal processes along with assigned responsibilities. This system will be the basis of design and implementation of a human behavior analysis system to be integrated in later stages with a data model that illustrates the data model. The targeted model is expected to be a core component in real life applications that require prediction of human behavioral patterns such as recommendation systems that is capable of making product recommendations based on the analysis and prediction of customer actions, mood, attitude and other factors. In addition to smart systems that can predict human actions (driving actions for instance).

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