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Improved Intention Discovery with Classified Emotions in A Modified POMDP

Sivaraman Sriram
University of Windsor

Improved Intention Discovery with Classified Emotions in A Modified POMDP-Based Dialogue System

by

Sivaraman Sriram

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Sivaraman Sriram

APPROVED BY:

_____

Dr. Kenneth Cramer
Department of Psychology

_____

Dr. Scott Goodwin
School of Computer Science

_____

Dr. Xiaobu Yuan, Advisor
School of Computer Science

_____

Dr. Subir Bandhyopadhyay, Chair of Defense
School of Computer Science

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iii

ABSTRACT

Emotions are one of the most proactive topics in psychology, a basis of forceful conversation and divergence from the earliest philosophers and other thinkers to the present day. Human emotion classification using different machine learning techniques is an active area of research over the last decade. This investigation discusses a new approach for virtual agents to better understand and interact with the user. Our research focuses on deducing the belief state of a user who interacts with a single agent using recognized emotions from the text/speech based input. We built a customized decision tree with six primary states of emotions being recognized from different sets of inputs. The belief state at each given instance of time slice is inferred by drawing a belief network using the different sets of emotions and calculating state of belief using a POMDP (Partially Observable Markov Decision Process) based solver. Hence the existing POMDP model is customized in order to incorporate emotion as observations for finding the possible user intentions. This helps to overcome the limitations of the present methods to better recognize the belief state. As well, the new approach allows us to analyze human emotional behaviour in indefinite environments and helps to generate an effective interaction between the human and the computer.

DEDICATION

To my dear friends and family

ACKNOWLEDGEMENTS

TABLE OF CONTENTS

CHAPTER

  I INTRODUCTION

  II PRECURSORY

  III BACKGROUND WORK

LIST OF FIGURES

LIST OF TABLES

CHAPTER I

INTRODUCTION

1.1 Big Picture

The recent buzz word in human-computer interaction research is the recognition of human emotion. Emotion classification has its own usage in making the conversation between the human and the computer even more interactive and pragmatic; and more importantly the system can respond appropriately to his/her emotional feelings [1]. According to Myers [2], emotions are "the complex psycho-physiological experience of an individual's state of mind as interacting with biochemical (internal) and environmental (external) influences". As well he stated that "in humans, emotions fundamentally involve physiological arousal, expressive behaviors and conscious experience". There are many applications in which this can have a major contribution such as a human-like robot that interacts with the user, 3D animations, and graphical designs in cinema.

Recognition of emotions can be done using different media of inputs. Some kinds of media are speech, gestures and textual inputs and so on. Each medium has its own variety of recognition and both advantages and disadvantages. For example, considering the textual medium, the chat text must either contain an emotional keyword or we could use machine learning approaches, e.g., Knowledge-based Artificial Neural Network (ANN), to mine emotions from the text [3]. Basic emotions such as neutral, fear, anger, sadness, surprise, disgust and joy can also be deduced using facial recognition approach [4]. In comparison, another source of information is emotional keywords because textual

1

emotions and direct emotional words such as 'HAPPY' are helpful for emotion recognition. In addition, emotional dataset labelled with semantic and syntax tags have been used for facial recognition [4].
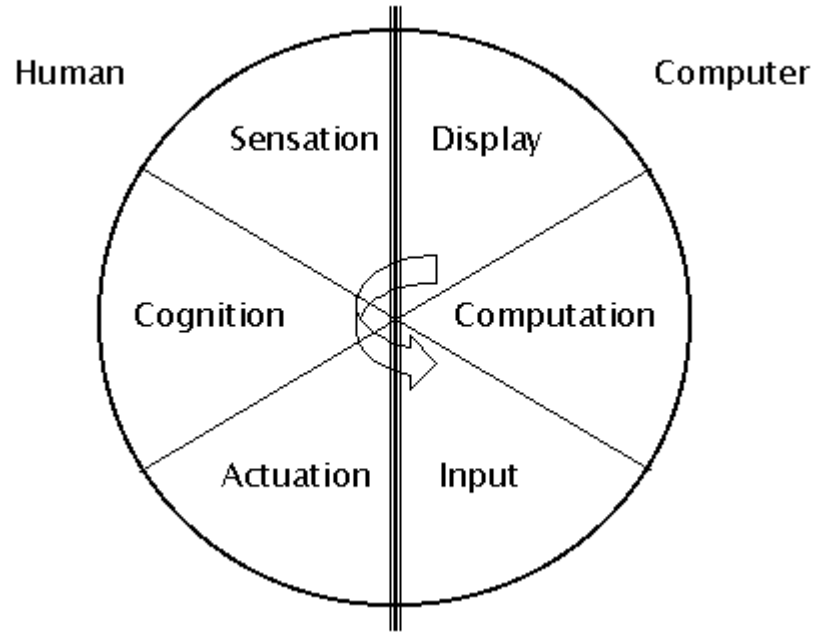
Figure 1.1.1: Human-Computer Interaction Diagram [5]

The belief state is a probability value that refers to the state of the environment at a given timestamp. Inferring the belief state in a dialogue conversation using any formatted medium (maybe even combined) is necessary to make the conversation look more like human-human interaction which is the bench mark for human-computer interaction. Figure 1.1.1 shows the important features of human-computer interaction as a circle separated into six equal pie wedges [5]. The belief state deduction of a human who interacts with a computer can be added up to a multimodal dialogue manager in order to make the conversation more appropriate and natural. For example, knowing the state of belief of a customer buying an online product would be helpful in giving him the suitable

2

offers with respect to the product. A multimodal dialogue system is a computational device or agent that engages in interaction with other human, uses human language in some form such as speech, text, or gesture and typically engages with human such interaction across multiple turns or sentences [6]. A detailed explanation about the multimodal dialogue manager is given in Section 2.2 of this thesis.

1.2 Problem Specification

Numerous methods of dialogue management have been proposed in the last two decades, including the traditional approach based upon Finite State Machine (FSM) and the more recent approach built upon the prevalent Partially Observed Markov Decision Process (POMDP) model. Finite state machine based approach is suitable to the tasks that are finely organized and is not flexible. Frame based approach uses one frame at a given instance to observe and record the information and is much better with respect to flexibility when compared to FSM based method [7]. These approaches still do not have a comprehensive solution to solve decision or uncertainty based problems. Hence Bayes network and/or Markov decision process based approaches are used to solve some uncertainties and probability based problems to some point but still have disadvantages such as imperfections in solving reflection uncertainties [4]. Even though POMDP is the existing popular approach, it still has its own difficulties that have to be dealt with to improve its performance. Regardless of its identified problem of scalability, this approach establishes undisputable benefits in handling the input of uncertainty over other known approaches. However, the current method has a domain knowledge base in the planning process, and uses not only the current, but also the previous belief state for the

3

determination of actions; the approach still did not quite completely understand user's intention as it does not consider the emotional states of the user. In an outlook, the POMDP-based approach only models the user and maintains the knowledge at the control level of a process but does not consider the fact that the interacting user has more than just conditional decisions. This thesis introduces human emotions as an observation and also considers historical beliefs as factors into the planning process of the POMDP to determine the actions and possible states, consequently improves the approach stated above.

1.3 Motivation

The Partially Observable Markov Decision Process (POMDP) is a mathematical model for sequential decision problems in partially observable environments. The term 'partial' means that the state of the world cannot be sensed directly [6]. The acceptance of embodied agents with a dialogue manager such as the POMDP depends on the naturalness and smoothness when interacting with users. Information about user emotion helps to discover the user intention, but has not been used in even the currently most advanced dialogue manager, due to the omission of history information in POMDP models. Thus the current techniques in solving a problem using POMDP based approach has its own limitations which gives an opportunity to come up with a better approach to solve the problem by modifying the existing methodology. This thesis conducts an investigation on this particular method and tries solving the challenges associated with the prevailing POMDP based dialogue manager.

4

1.4 Contribution

In this thesis, two main contributions have been made. First, the emotions of the interacting user is estimated using a customized decision tree algorithm from using different input methods such as text and speech forms. Second, with drawing the conclusion that a POMDP based approach drops some noteworthy evidence in terms of the historical information space theory with additional observations, the modified POMDP-based dialogue management approach is proposed to handle the uncertainties in the belief state. As well, it helps to improve the precision of determining user's intention using the recognized emotions. Experiments under different scenarios are conducted to evaluate the suggested technique. The results obtained from different experimentation support this notion and validate that the proposed approach accomplishes the expected results.

1.5 Consolidation of Thesis

The remainder of this thesis is structured as follows: Chapter 2 briefly reviews the general multimodal dialogue management and its components. Chapter 3 presents a survey of prior works that are related to the proposed method in two different parts, i.e., emotion recognition and user intention discovery. Chapter 4 states the research objectives and shows the need of user's emotion as an observation in discovering intention and belief update. Finally chapter 5 describes the implementation of the dialogue management with modified POMDP incorporating the emotions in the prediction of belief state. It also demonstrates experimental results.

CHAPTER II

PRECURSORY

2.1 Human Emotions and Classification

Emotions are a basis of forceful conversation and divergence according to the earliest philosophers and other thinkers to the present day. Myers [2] states that the emotions arise from physiological and psychological excitement. This statement can be explained simply by saying that the happiness comes from smiling and the sadness comes from crying. Classification of human emotions has become an increasingly important element for affect-sensitive human-computer interaction. The components of emotion are distinguished on the basis of physiological or psychological factors and include emotion faces, elicitors, and neural processes. Primarily, emotions are classified into six basic types: joy, disgust, surprise, anger, sadness and fear [8] as shown in Figure 2.1.1. We employ neutral emotion in computer science to represent a no-emotion state [9]. This is because the system involves textual/spoken data in predicting emotions in which if a particular sentence does not provide enough information for estimation, then the concluding result would be a neutral emotion.

6
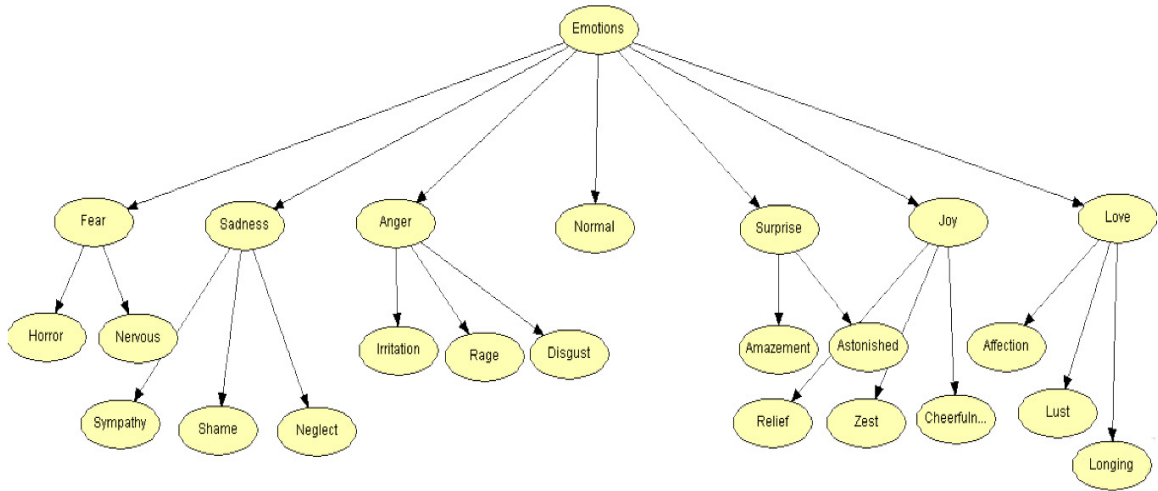
Figure 2.1.1: Customized Tree with Emotional Nodes (Primary and Secondary) [8]

The secondary state of emotions is described using a tree structure, which is inherited from their respective primitive types. These emotions can be recognized and classified using various sets of input levels such as textual conversations, speech based recognition, facial recognition and dynamic gesture recognition capturing the human body movements.

2.2 Multimodal Dialogue Management

2.2.1 Input

Multimodal systems have various modalities with respect to input modes such as speech, facial expressions, gestures, gazes etc. We have two kinds of inputs, namely, active input modes and passive input modes. Active input modes are explicit commands of user's intentions such as speech. Passive input modes refer to the user's behaviour that

7

is recognized by the computer like facial expressions and manual gestures. They involve user inputs with no explicit commands and monitors passively.

2.2.2 Fusion

The input nodes give the information extracted from the user for extraction, recognition and integration. In this module the agent processes the information and assigns a semantic representation which is eventually sent to the dialogue manager. Fusion is classified into two categories: feature-level fusion and semantic-level fusion. The first one is a method for fusing low-level feature information from parallel input signals within a multimodal architecture like feature extraction. The second one is a method for integrating semantic information derived from parallel input modes in a multimodal architecture like action recognition (speech, gestures, so on). Low-level fusion is a sensory fusion in which sensory data from the sources results in better information as an output, while semantic-level fusion in the dialogue manager needs a knowledge source which already has a collective familiarity about the input .

2.2.3 Dialogue Manager and General Knowledge

A dialogue manager is the core component of a dialogue system. It maintains the history of the dialogue, adopts certain dialogue strategies, retrieves the content stored in files or databases, and decides on the necessary response to the user. The dialogue manager creates and updates an Information State corresponding to a notion of dialogue context. The dialogue moves have the effect of updating information states and moves

can be initiated. The term "dialogue context" can be viewed as the totality of conditions that influence the understanding and the generation of communicative behaviour.
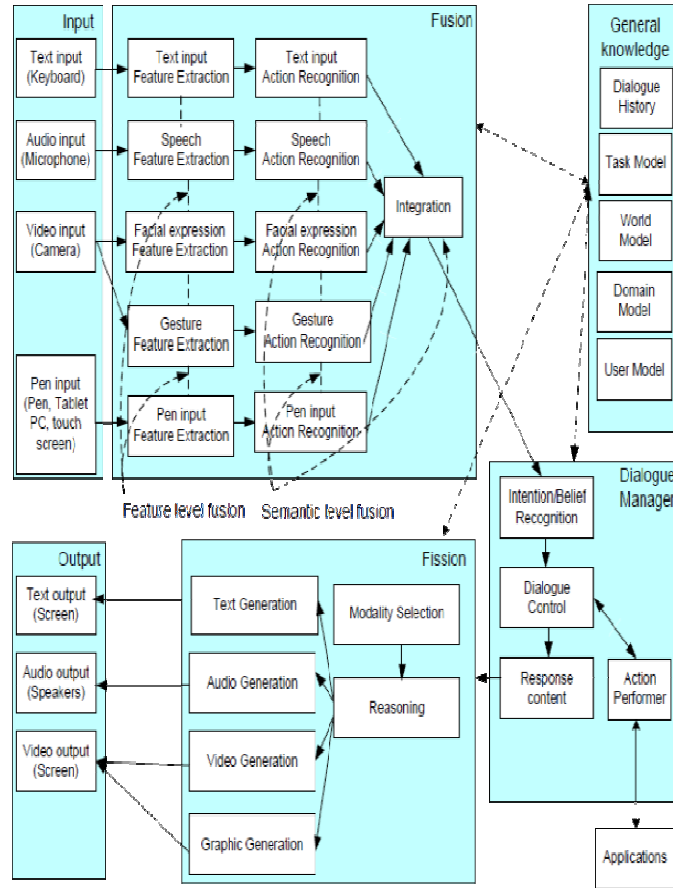
Figure 2.2.1: Multimodal Dialogue Manager Flow Chart [7]

The main tasks are updating the dialogue context on the basis of interpreted communication, deciding what content to express next and when to express it and interfacing with task/domain processing. A number of general knowledge sources is used by the dialogue manager such as Fusion and Fission which forms the overall *dialogue* history, task model, world model, domain model and user model. The dialogue model is a set of historical record of the spoken/ textual dialogue so far in terms of the entities. This

9

representation provides a basis for conceptual coherence. Task model is a representation of the information to be gathered in the dialogue. This record, often referred to as a form, template, or status graph, is used to determine what information has not yet been acquired. World model contains general background information that supports any commonsense reasoning required by the system. Domain model uses the specific information about the domain; user model may contain relatively stable information about the user that is relevant to the dialogue such as the user's age, gender, and preferences as well as information that changes over the course of the dialogue, such as the user's goals, beliefs, and intentions. Figure 2.2.1 shows the process flow of the multimodal dialogue manager.

2.2.4 Fission

Fission is a process of understanding an abstract message from the dialogue manager in which the information is in machine understandable format. The tasks of a fission module are composed of three categories. The first is for content selection and structuring, in which the presented content must be selected and arranged into an overall structure. The second is for modality selection, which determines the optimal modalities based on the current situation of the environment. For example, when the user device has a limited display and memory, the output can be presented as the graphic form such as a sequence of icons. The third category is for output coordination, which is responsible for the coordination of all the output channels that the resulting output forms a coherent presentation.

2.2.5 Output

Many ways of output modalities can be used to present the information content from the previous module such as: speech, text, graphics, avatars etc. Some of the common output combinations are: speech and text, speech, text and graphics, speech and gestures, graphics and avatar, text and graphics, speech, graphics and animation.

2.3 Agents, Belief States and User Intentions

In artificial intelligence, an intelligent agent is an autonomous entity which observes and acts upon an environment and directs its activity towards achieving goals (Goal Oriented Agents). Intelligent agents may also learn or use knowledge to achieve their goals. Agents are often classified into two categories according to the techniques they employ in their decision making: *reactive* agents base their next decision solely on their current sensory input; *planning* agents, on the other hand, take into account anticipated future developments, for instance as a result of their own actions to decide on the most favorable course of action. The software agent we are using in this research is reactive as well as a planning agent, which can be obtained using different styles of agent modeling.

The belief-desire-intention (BDI) model has come to be possibly one of the well known and studied models of practical reasoning agents. There are several reasons for its success, but perhaps the most compelling is that the BDI model combines a respectable philosophical model of human practical reasoning as originally developed by Bratman [11]. The explicit goals to achieve and events to handle are the desires of agents. A set of *plans* (*intentions*) is used to describe how agents achieve their *goals*. Each *plan* describes

11

how to achieve a *goal* under varying *environments* (*belief*). A set of data called *belief* describes the *state* of the *environment*.

Stanford's philosophical encyclopaedia states that [12] "Belief state or state of belief is considered as the propositional attitude of the user interacting with an agent". According to Brown [13], a state of belief is a primary bearer of truth-values in every given instant of time and propositions being its object. It is also conditioned that the belief state of an organism (human in our case) depends on two factors. The first condition is that the belief state of the user at a given time frame should supervene on his/her intrinsic properties. Secondly, a belief state must be a state of the user that depends only on those facts that are relevant to what he/she believes. Thus a proposition at a given time slice depends on the total state and the current situation. If we could deduce this proposition which is nothing but the belief state at a given instance of time or a particular situation, then the positive sum of all proposition divided by the number of instances would present the overall belief state. Figure 2.3.1 shows an overall state diagram for a given instant of time.
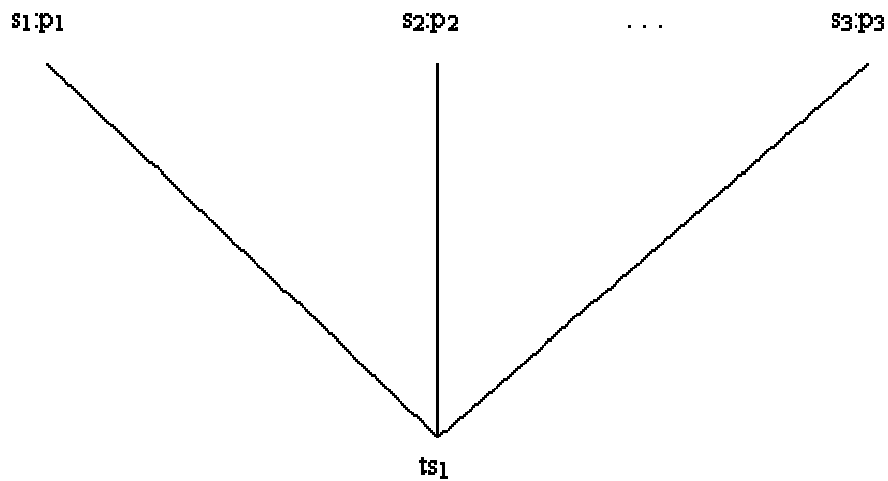
Figure 2.3.1: Overall State for a Given Time Slice [13]

In order to assist the user effectively to search on what they need and also learn the necessary methodology, the computer needs to understand the user's intention. Thus the belief state that we specify above is the intentional probability of the user. The user's intention can be classified into two different levels: *Action* intention and *Semantic* intention. Action intentions are lower level, such as mouse click, keyboard typing and other basic actions performed on a computer. Semantic intentions correspond to what the user wants to achieve at high level, which may involve several basic actions on a computer to accomplish it. In this thesis we concentrate more on semantic level intentions.

13

CHAPTER III

BACKGROUND WORK

3.1 Emotion Recognition from Different Input Types

This chapter is dedicated for highlighting major contributions from previous work in the field of emotion recognition. Seol [3] proposed a method for recognizing emotions from a textual data by using knowledge-based Artificial Neural network, which was hybridized with the traditional keywords based search to improve the efficiency which is shown in Figure 3.1.1.
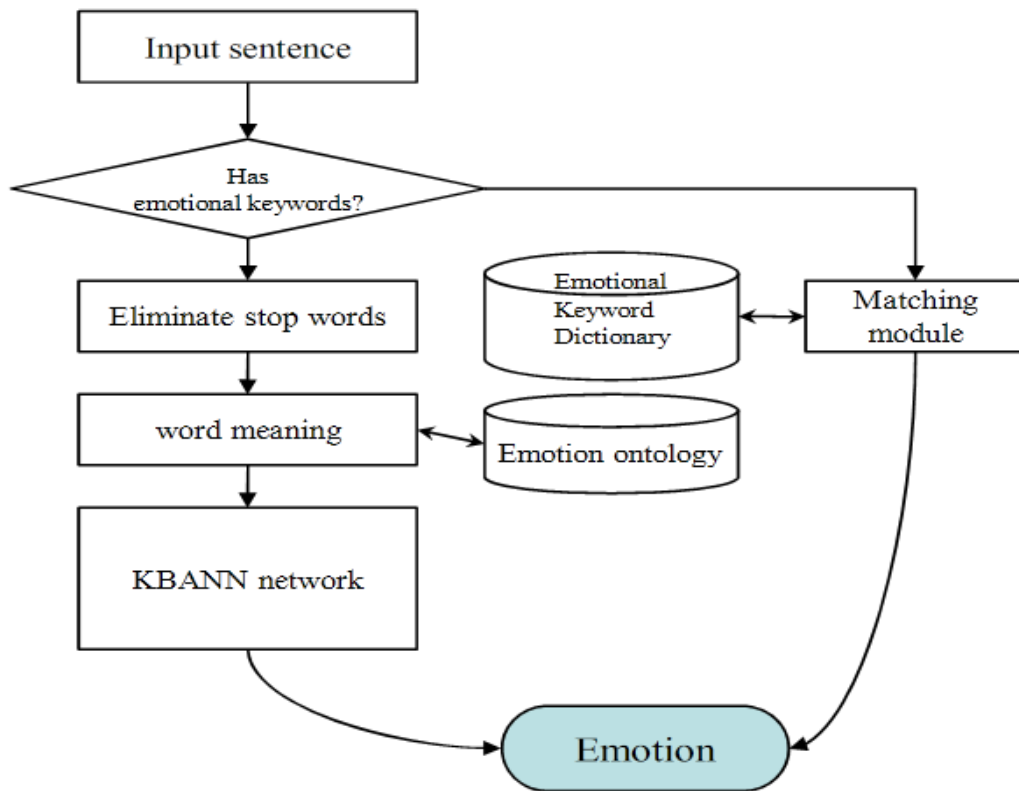
Figure 3.1.1: Emotion Recognition Process in Hybrid Keyword Approach [3]

Chunling [8] gave a preliminary method in estimating the emotion in a text based chat system using the split keywords based searching which has client-server architecture as shown in Figure 3.1.2.
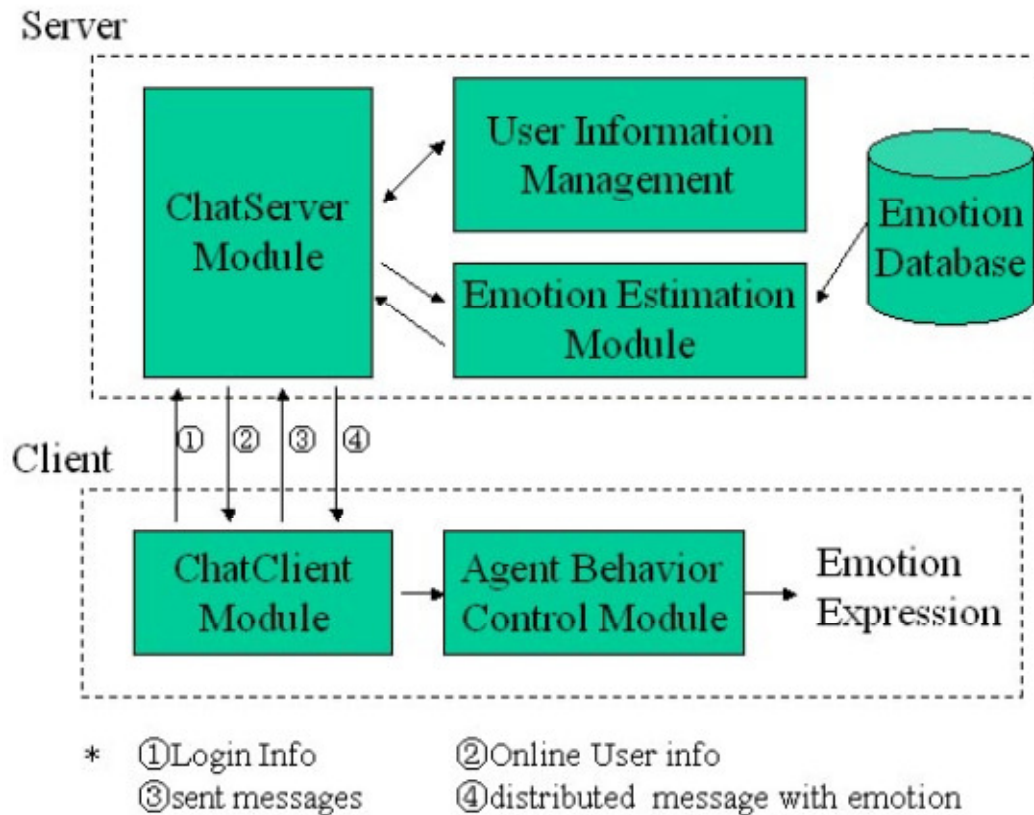
Figure 3.1.2: Split Keyword based Emotion Recognition System [8]

Yu- Lu [14] designed a system which uses a semantic role labeling system that finds the all-important constituent in each paragraph and then identifies the emotion using web mining. His research is useful in a textual emotional mining but the method utilizes a lot of memory and also uses a web based search like Google. Wu [15] proposed an approach for automatic recognition of emotions from the text in which emotion generation rules (EGRs) are manually deduced to represent the conditions for generating emotion. Based on the EGRs, the emotional state of each sentence can be represented as a

sequence of semantic labels (SLs) and attributes (ATTs); SLs are defined as the domain-independent features, while ATTs are domain-dependent.

Wong [16] presented a novel approach for recognizing facial emotion in order to further detect human suspicious behaviors. Instead of relying on relative poor representation of facial features in a flat vector form, the approach utilizes a format of tree structures with Gabor feature representations to present a facial emotional state. Cheng [17] proposed an automatic facial expression recognition system. This system develops a semantic-based learning algorithm using the analytical hierarchy process (AHP), which is created to bridge the gap between low-level visual features and high-level semantics. Jamshidnajad [18] presented a facial expression recognition model using fuzzy techniques in order to further detect human behaviors in the e-business. A fuzzy clustering model is proposed to classify images after extracting the features that are used as inputs into the classification system. The outcome of this model is one of the preselected emotional categories within the given image set.

Castellano [19] proposed an approach for the recognition of acted emotional states based on the analysis of body movement and gesture expressivity showing that distinct emotions are often associated with different qualities of body movement. He used non-propositional movement qualities to infer emotions and propose a method for the analysis of emotional behaviour based on both direct classification of time series and a model that provided indicators describing the dynamics of expressive motion cues. Egges [20] described a generic model for personality, mood and emotion simulation for conversational virtual humans. He presented a generic model for updating the parameters related to emotional behaviour and gave a linear implementation of the update

16

mechanism. He also explored how existing theories for appraisal can be integrated into the framework to form a prototype in combination with a dialogue system and a talking head with synchronized speech and facial expressions. Devillers [21] reported on three studies: the first concerns the use of multi-level annotations including emotion tags for diagnosis of the dialogue state; the second investigates automatic emotion detection using linguistic information; and the third reports on two perceptual tests for identifying emotions as well as the prosodic and textual cues which signal them and lastly propose a new set of emotions.

3.2 The Flat POMDP Model

The POMDP models an agent taking a sequence of actions under uncertainty to maximize its reward. Formally it is specified as a tuple(S, A, O, T, Z, R, γ), where S is a set of states, A is a set of actions and O is a set of observations. In each time step, the agent lies in some state $s \ \varepsilon$ S; it takes some action $a \ \varepsilon$ A and moves from s to a new state s'. Due to the uncertainty in action, the end state s' is modeled as a conditional probability function $T(s, a, s') = p (s'| s, a)$, which gives the probability of which the agent lies in s', after taking action 'a' in state s. The agent then makes an observation to gather information on its state. Due to the uncertainty in observation, the observation result o which belongs to O is again modeled as a conditional probability function $Z(s, a, o) = p(o| s, a)$ [6] [22].

In each step, the agent receives a real-valued reward R(s, a_m), if it takes action 'a' in state s, and the goal of the agent is to maximize its expected total reward by choosing a suitable sequence of actions. For infinite-horizon POMDP, the sequence of actions has infinite length. It also specifies a discount factor γ belonging to [0, 1) so that the total

17

reward is finite and the problem is well-defined. In this case, the expected total reward is given by E [P(t) γ(t) R(s_t, a_t)] where s_t and a_t denote the agent's state and action at time t. A policy π induces a value function V(b) that specifies the expected total reward of executing policy π starting from b. It is known that V*, the value function associated with the optimal policy π∗, can be approximated arbitrarily closely by a convex, piecewise-linear function V(b) = max ∈ L(α.b), where L is a finite set of vectors called α-vectors, b is the discrete vector representation of a belief, and 'α.b' is the inner product of vectors α and b. Each α-vector is associated with an action. The policy can be executed by selecting the action corresponding to the best α-vector at the current belief. Therefore a policy can be represented by a set of α-vectors. Figure 3.2.1 shows the flow of the POMDP model.
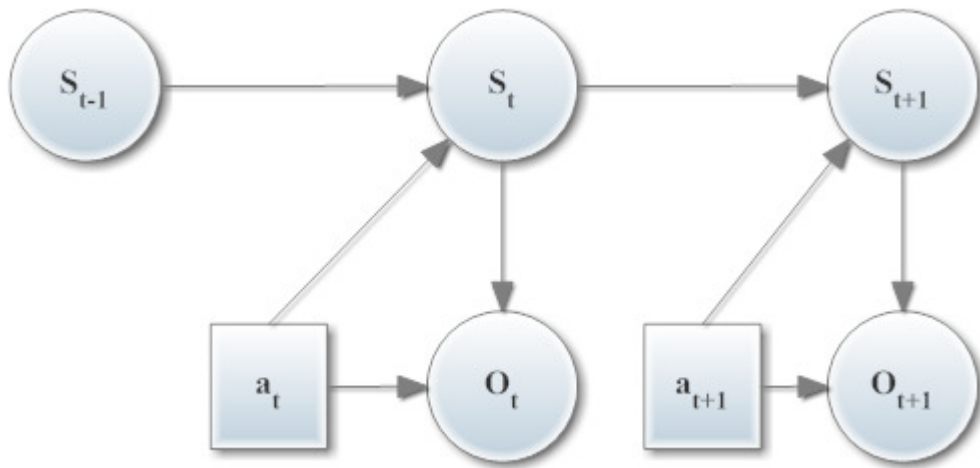
Figure 3.2.1: POMDP Model [23]
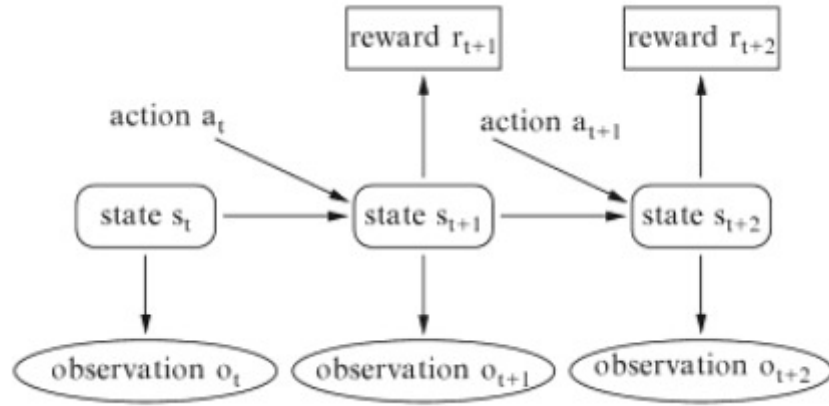
Figure 3.2.2: Transition of States in POMDP Model with Action and Observation

The state estimator component of a POMDP updates the belief state of the agent every time it executes an action. Given the belief state of the agent at time t as b_t, it gives an opportunity to compute the belief state at time $t + 1$, b_{t+1}, after a transition in the process where the agent occupies state S, executes an action *a* and perceives an observation *z* which is shown in Figure 3.2.2 [23]. The belief that the agent is in the resulting state s' is derived by:

$$b_{t+1} = P(s'|z, a, b_t)$$

$$= \frac{P(z|s', a, b_t)P(s'|a, b_t)}{P(z|a, b_t)}$$

$$= \frac{P(z|s', a, b_t)\sum_{s \, \varepsilon \, S} P(s'|a, b_t, s)P(s|a, b_t)}{P(z|a, b_t)}$$

$$= \frac{P(z|s', a)\sum_{s \, \varepsilon \, S} P(s'|s, a)P(s|a, b_t)}{P(z|a, b_t)}$$

$$= \frac{O(s', a, z)\sum_{s \, \varepsilon \, S} T(s, a, s')b_t(s)}{P(z|a, b_t)}$$

19

In essence the above equation evaluates the probability of ending up in states given that the agent had a belief about its own state b_t, executed an action and perceived an observation z according to the predefined observation and transition functions of the POMDP, O() and T() respectively. The denominator $P(z \mid a, b_t)$, is a normalizing factor and is equal to the total probability of perceiving the observation z given the previous belief state of the agent and the action it executed:

$$P(z \mid a, b_t) = \sum_{s' \varepsilon\, S} P(z|s',a)P(s'|s,a)b_t(s)$$

$$= \sum_{s' \varepsilon\, S} O(z,s',a)T(s,a,s')b_t(s)$$

3.3 Information State Space Approach

A finite state model based dialogue system is one of the primitive dialogue management approaches. The system directs the user with prearranged questions designed by the developers to complete some task. Finite State Machine (FSM) based approach models the dialogue flow and task representation with nodules and edges. Each nodule in the model stands for the system utterance and the edges keep in touch to the user's answers which establish all possible paths through the set of connections. This approach is the most familiar and simple model. The framework collects one piece of information at a time. Before submitting all the information to knowledge base or database it will definitely confirm with the user. Both task model and dialogue model are inherent and they are programmed by a dialogue designer. Baekgaard [24] discussed this model and applied this approach in the Danish dialogue project. They have used a basic finite state set-up to model the dialogue flow for a repeated book club service. More

20

details about the theory of this model are described in [25]. A dialogue model in the domain of the train ticket issuing system will be used in the following of this section to illustrate the various dialogue management approaches. In this domain, the ticket can be issued after both departure city and arrival city information obtained. Figure 3.3.1 illustrates the finite state machine based approach of dialogue management under above mentioned domain.
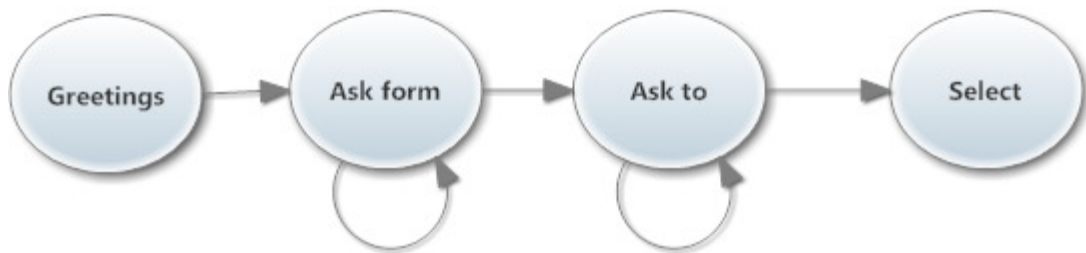
Figure 3.3.1: FSM based Dialogue Management Example [25]

McTear [26] pointed out that the palpable advantage of the finite state model approach is effortlessness and only suitable for the thought through task. The questions to be asked and their sequences are predetermined. In the whole dialogue session, the agent guides the user and constrains the layout of the user's answers. After each turn in the dialogue, the agent will explicitly interpret with the user what have been assumed presently. As there are so many restrictions within the dialogue, the agent does not require sophisticated knowledge applied such as natural language processing. The advantage of the finite state based approach meanwhile reflects the shortcomings including: it can only apply to the uncomplicated domain as it lacks flexibility in the dialogue management. During the dialogue, the user neither manipulates the dialogue nor brings in new dialogue subject. When more uncertainties are brought by the users or environment, the system can easily crash because of the unsuitable dialogue policy

21

generated by the domain's expert and restricted stipulated script. In finite state based approach, the dialogue system is agent directed and only collects each section of information at every turn based on its current dialogue state. When the user introduces more information than the system necessitates at each dialogue state, there exists a problem. Finite state machine based approach neither realizes the manifold slots filling nor deals with the outmoded information brought by the user. As an annexe of finite state based model, frame-based model is developed to prevail over the lack of flexibility of the finite state machine based method. The frame-based approach is like a task of slot-satisfying where a slot is an encoded set of information that should be congregated by the agent. The dialogue is conducted to fill in the vacant slots. It also allows some amount of mixed-initiative and several slot fillings, which decides the dilemma within the approach. However, the conversation model is still programmed by a dialogue designer based on their familiarity and consideration. The frame based approach is illustrated in Figure 3.3.2[6]:
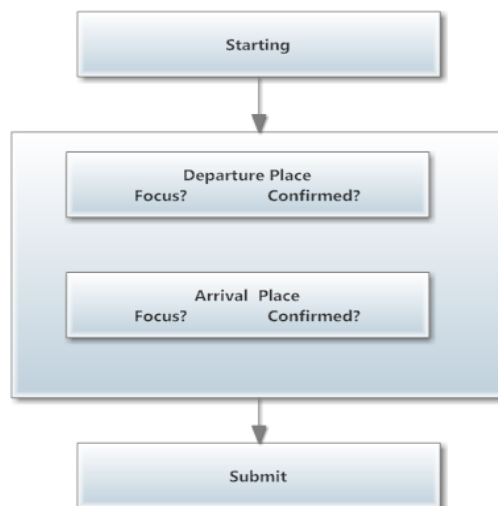
Figure 3.3.2: Frame based Approach Example

22

Ward and Pellom [27] used the analogous mechanism in their raconteur system, in which the next action of the agent is produced based on the current framework rather than stipulated script. Jonsson [28] used information requirement forms under the sphere of influence of bus timetable information system. A more flexible frame based approach was projected by Goddeau [29] named '*E-form*' which has been applied in a spoken language boundary to a classified advertisements for used car database. He also abridged other variations of frame-based models which tolerate to deal with other complex dialogues. These variants include schemas that are used in the Carnegie Mellon Communicator system to represent more multifarious tasks [30] [31] and task structure graphs which provide a semantic structure and are used to determine the behaviour of the dialogue control as well as the language understanding component [32]. Type hierarchies are used to model the domain of a dialogue and as a basic for clarification questions [33]. Blackboard is used to manage contextual information applicable to dialogue manager such as history board, control board, presentation board, etc [6]. Frame based approach can comprehend the mixed imitative dialogue and put up with redundant information brought by the users. The sequence of the questions or the information to be gathered is not pre-fixed, which is based on the current context to generate next query to ask. However, McTear [26] summarized that the next step that is based only on the existing context is not enough. Hence he suggested a problematical domain in which the state of the world is dynamic and the knowledge level of the user is diverse which can not apply for the classical frame based approach.

3.4 Factored POMDP Approach

William [34] casted the spoken dialogue system as a factored POMDP to use this model as general framework for existing POMDP dialogue manager. In this model, the POMDP state variable $s \; \varepsilon \; S$ into three components such as: 1) the user's goal, $s_u \; \varepsilon \; S_u$; 2) the user's action $a_u \; \varepsilon \; A_u$; 3) history / state of the dialogue $s_d \; \varepsilon \; S_d$. Thus, the POMDP state 's' is given by the tuple (s_u, a_u, S_d). As well, from the system's perspective, all those components are unobservable. The user's goal, s_u gives the current goal or intention of the user. For example, user goal includes a complete travel schedule, a product the user would like to purchase or requesting information about it and so on. The user's action a_u, gives the user's most recent actual action. For example, identifying a place the user would like to travel, replying to yes/no question, or a null response indicating the user took no action. The dialogue history/state S_d, indicates any relevant history or state information. For example, if a particular slot has not been stated and if there are any ungrounded items then the dialogue designer might wish to penalize asking an open question. The POMDP action $a_m \; \varepsilon \; A_m$ is the action the machine takes in the dialogue such as greeting the user or asking a query. At each time stamp, the POMDP receives a single observation but it maintains a distribution over all possible user actions a_u. The factored POMDP is given by decomposing the POMDP transition function which is as follows:

$$P(s'|s, a_m) = P(s'_u, s'_d, a'_u|s_u, s_d, a_u, a_m)$$
$$= P(s'_u|s_u, s_d, a_u, a_m)P(a'_u|s'_u, s_u, s_d, a_u, a_m)P(s'_d|a'_u, s'_u, s_u, s_d, a_u, a_m)$$

The first term points out the user goal model. At each time step t, it is assumed that the user's goal depends on the previous goal and the machine action.

24

$$P(s'_u|s_u, s_d, a_u, a_m) = P(s'_u|s_u, a_m)$$

The second term is the user action model which indicates what action the user is likely to take at each time step *t*. It is assumed that the user's action depends on the current goal and preceding machine action.

$$P(a'_u|s'_u, s_u, s_d, a_u, a_m) = P(a'_u|s_u, a_m)$$

The third term is the dialogue model which indicates how the user and system actions affect the dialogue history. The current state or history of the dialogue depends on the previous history / state of the dialogue, user's action and system action. Thus, the transition function of POMDP is given by,

$$P(s'|s, a_m) = P(s'_u|s_u, a_m) |P(a'_u|s'_u, a_m) P(s'_d|a'_u, s_d, a_m)$$

The observation function of POMDP is given by,

$$P(o'|s', a_m) = P(o'| s'_u, s'_d, a'_u, a_m)$$

The confidence score and rewards are not specified as this model is associated with a particular user goal and designated objectives of the target system respectively. At each time *t,* the actions are selected depending on the belief state to maximize the cumulative long-term reward by substituting and simplifying the above equations. The belief state of the next state is given by,

25

$$b'(s'_u, s'_d, a'_u) =$$

$$k. P(o'|a'_u)P(a'_u|s'_u, a_m) \sum_{s_u \, \varepsilon \, S_u} P(s'_u|s_u, a_m) \sum_{s_d \, \varepsilon \, S_d} P(s'_d|a'_u, s_d, a_m) \sum_{a_u \, \varepsilon \, A_u} b(s_u, s_d, a_u)$$

This model is tested with a simulated dialogue management problem in a travel domain in which the user is trying to buy a ticket to travel and compared the results with handcrafted policies and MDP baseline [23] [35]. The results showed that POMDP maintains a well formed distribution over user goals and in case of uncertainty. In particular, it reflects the true user goals. However, since this model assumes the flat listing of flat components, the spoken dialogue systems with hierarchical components may result in poor performance.

3.5 Hollnagel's Contextual Control Model (COCOM)

Hollnagel [36] initiated the contextual control model to assess team behaviour based on the time available. The main contribution was that the system determined the actions based on the context of the situation and available time. He classified team behaviour into four different modes:

- Scrambled Mode

- Opportunistic Mode

- Tactical Mode

- Strategic Mode

26

Hollnagel's COCOM was tested by Stanton, et al. [37] where they created 24 groups of people with 4 people in each group. There were 74 males and 22 females between 19 and 55 years of age. They made six groups of four people in each group to work on balancing a simulated gas network system. As an outcome of this experiment they reliably categorized the four control modes and showed that the progression between control modes conformed to a linear progression.

Shown in Figure 3.5.1 is the COCOM model, featuring the movements available between the different control modes. We have applied the same COCOM to the proposed model for creating a mock-up data and testing it with the real time POMDP based solver.
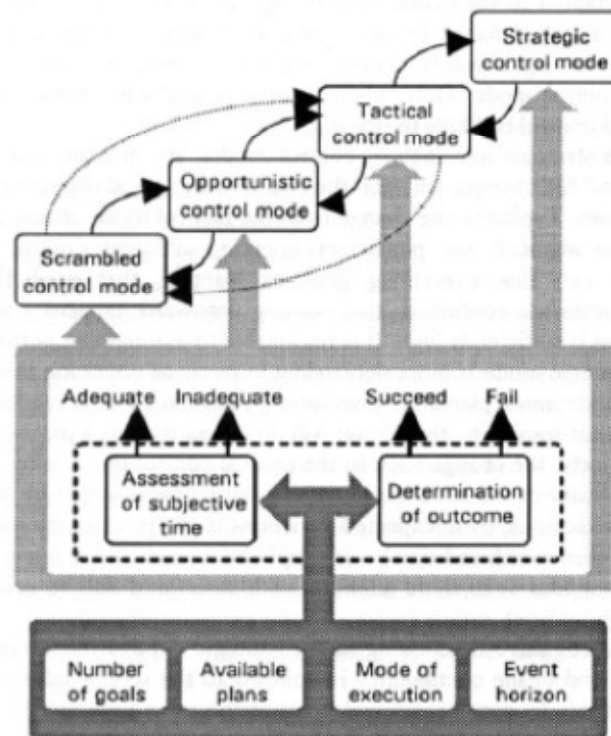
Figure 3.5.1: Flow of the Four Contextual Control Modes (COCOM) [36]

3.6 Modified Partially Observable Markov Decision Process

The Modified POMDP model was established to overcome the limitations of the existing POMDP approaches. According to Sabiha [7] the existing POMDP approaches considered the world to be static and always made their decisions based on the current belief state. It was also pointed out how the existing POMDP approaches ignored the dialogue history to make decisions effectively. Hence the author proposed a new POMDP based approach known as the Modified Partially Observable Markov Decision Process which shared Hollnagel's Contextual Control Model (COCOM) for decision making based on user input [36].

The dialogue manager toggles from one mode to another for processing user queries. For example, if the dialogue manager is not able to recognize the user request it switches to the scrambled mode where panicking occurs. The dialogue manager will attempt to move to tactical mode by giving the user a set of alternative options whereas other dialogue managers try to replicate the same question again and again until the user comes up with the right answer forming an infinite loop.

The dialogue manager attains the goal by changing over from one mode to another using forward planning. The lowest level of control will be the scrambled control mode where the system does not have a proper understanding of the user's queries and the most desirable level of control mode will be strategic mode where the system has a clear understanding of the user's queries. The system chooses the best action based on the context of the dialogue conversation and transitions between the modes depending on the dialogue states, current action, context of the situation and available time. The system provided evidence for being effective in handling the uncertainty caused by speech

28

recognition errors and performed much better at handling conflicts in comparison to the existing POMDP approaches.

3.7 A Historical Information Approach of POMDP based Dialogue Management

The existing approaches of the dialogue management suffer from inflexibility during human-computer interaction as in FSM-based approach. They also lack the ability in handling any ambiguity as in frame-based and bayes-network approaches, and exhibit insufficiency when dealing with uncertainties as in the POMDP-based approach. To overcome the shortcomings while retaining the advantages of POMDP-based approaches, Bian [6] [38] proposed a modified planning strategy as illustrated below

$$\Pi_{new}: \ I_{k-1} \cup I_k n \rightarrow U$$

In the new approach, both I_k and I_{k-1} are still in the form of belief state, and state updating still uses the existing POMDP model as described. The addition of I_{k-1} in the modified approach, however, introduces an important element to dialogue management, i.e., the history of belief state or the dynamics of belief state. Although the historical information of observations and actions is not maintained explicitly in I_{k-1}, the union I_k and I_{k-1} in the above equation diminishes the negative effect of Markov assumption and allows POMDP-based dialogue management to plan for actions with not only the current belief state but also the updated history before reaching the current state. The uncertainties that the original POMDP-based approaches fail to handle mainly arise from situations in which the user lacks knowledge in the domain or the user's goal cannot be fulfilled due to real-life constraints. In addition, dependency of factors in belief state also causes uncertainty.

29

The original POMDP-based approach is only able to resolve those uncertainties that are brought in by noise from observations, e.g., misinterpretation of words, and actions, e.g., misunderstanding of meaning. The dialogue system tries to "listen correctly" and to response appropriately to the user based on its state of belief [39]. By interrupting the planning process of POMDP-based dialogue management, a new component can be added to introduce a knowledge base with new rules and a database with practical constraints. Shown in Fig. 3.7.1 is the architecture for the modified POMDP-based dialogue management, in which the additional component interrupts the direct flow from b to π. As a realization of the new planning strategy, action alters the original action when there is an unexpected change from I_{k-1} to I_k, or more accurately from the previous belief state to the current state [38]. The added component also skips the original planner π and makes direct contact with the user. At each stage of a dialogue, the new approach uses the domain knowledge and constraint database to help validating the change of belief state. The structure for the approach is shown in Figure 3.7.1. After an initial greeting, the system always updates the belief state with previous belief state, the current action, and the latest observation from the user.
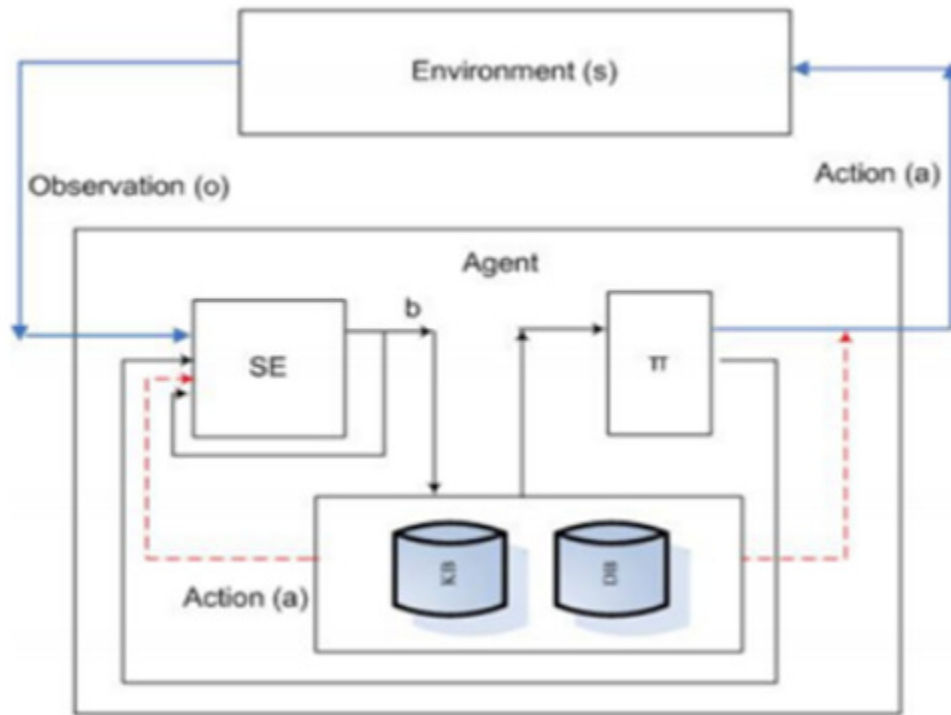
Figure 3.7.1: Modified POMDP Approach

If there is a failure in validation results a roll-back of belief state to the previous stage occurs, which means that the current state of the system will not be considered necessary to attain a particular user goal. Meanwhile, it triggers an explanation to the user and a question requesting for further information. This planning process is able to guide the user to reach a feasible goal that satisfies the need without causing conflicts.

3.8 Conclusion

In this chapter, we discussed briefly about different approaches of dialogue management, with emphasis on the more recent approaches based on POMDP and historical information space. While each of these approaches has its own advantages and drawbacks, there are still issues and limitations remaining unsolved. This thesis considers the historical information based POMDP model as the baseline and proposes a new method to overcome its disadvantages.

CHAPTER IV

PROPOSED WORK

Dialogue management is primarily delinquent under the influence of uncertainty. This chapter explains the proposed method of using the user's emotion to better predict the next possible belief state with the analysis of the history of user dialogues which is then used in the belief update. POMDP is the framework for agent planning under uncertainty and used for problem solving in dialogue management to make decision in the environment where the state of the agent is uncertain. POMDP can be used where the environment is noisy (one which has unnecessary information) and with the help of belief state the agent can reach a conclusion about the intension of the user. The problem with respect to dialogue management system needs the history to analyze the user intension in a better way and to reduce the uncertainty of the environment to the agent. This problem is solved with the help of the information space.

4.1 Shortcomings of the Current Techniques

The POMDP-based approach avoids the need to estimate system state by using a set of probability distribution over belief state in the planning process. Together with the action at the kth stage and the previous belief state, the system uses new observations to update the belief state and plans for action at the next stage. In the process, the states of both the system and the user are hidden in the information space. As defined earlier the flat model and the factored model, history information state is mapped to a probability

distribution over the unknown system state. As this conversion is based on the Bayes filter theory, which in turn is under the Markov assumption, the POMDP-based approach plans for actions with only the current belief state, which is clearly illustrated in the background work section. Planning with POMDP models is better than all the other existing approaches as it does not rely on estimated system state, and is able to handle input uncertainty. However, the elimination of $I_0 \cup I_1 \cup I_2 \cup I_3 \ldots \cup I_{k-1}$ from I_{hist} makes it impossible to trace changes in belief state and to retrieve the historical information of observations and actions. In other words, belief state is a static probability distribution over the current system state only. As a consequence, the POMDP-based approach is unable to deal with uncertainty in belief state itself, which corresponds to uncertainty in either user's actions or the observation of user's actions. In another perspective, the POMDP-based dialogue management approach only models the user's goal or it can be considered as a user modeling rather than a task modeling or machine state modeling. When we are dealing with the observation and action uncertainties, the POMDP-based approach outperforms the other approaches. This advantage is even more obvious when the error rate of the input is high. Let us consider a situation when listening to the user's goal is not correct at the beginning. The task will finally end up with the failure although dialogue model listens correctly. Usually the dialogue systems make an assumption that the user can always answer the questions from the agent. However, in the real life condition, the user might have a lack of domain knowledge and could provide unreasonable information to the agent. This situation will be worse when the user cannot actually understand the question generated by the agent. If the dialogue management approaches model the user alone without its own domain knowledge level inference, the

34

task cannot be achieved. In the process of the human-computer interaction, if the computer can appropriately influence the user and guide the user, the task is more probably to be achieved. These problems are overcome using the historical information space based approach for the POMDP but this method still does not consider the fact that the emotion of the user is important while deducing the next possible state. For example, the user's intention can be deduced to a particular scenario which could be suboptimal as it might be something which user does not want or might make him or her displeased or unsatisfied. This leads to the new proposed approach, which is to be explained in the next sub-section. In the proposed approach, the user's emotion is first inferred using a customized decision tree and these emotions are then perceived in the POMDP model as an observation including the action at every transition.

4.2 The New Proposed Method

This chapter gives a detailed explanation about the contribution of this thesis. After an overview of the proposed methodology, it discusses about the customized decision tree algorithm [1] and integration with spoken dialogue systems for decision making with user emotions inferred by this algorithm from known and unknown datasets. Details are then provided for a modified history space based (I_{hist}) POMDP approach, which becomes capable of predicting the user intentions when not only given user actions but also supplied with user emotions. To explain the customized decision tree process better, let us first give an overview of the standard decision tree model. Before we proceed further we would like to highlight the main contribution towards this thesis:

35

- *Classification of emotion of the given user's input (user action U_a) using customized decision tree algorithm.*

- *Introduce the inferred emotions to the spoken dialogue manager for decision making.*

- *Utilize the exiting modified POMDP approach which uses the historical information space to predict the overall state of belief or the user intention using not only the actions of the user but also the inferred emotions as an observation $(O_u + O_e)$.*

4.2.1 Overview of Proposed Architecture

Analysis indicates that the compact of I_{hist} of history information space into a resulting information space in a compressed form results in loss of important information [6]. The consequence is inflexibility for human-computer interaction as in the FSM based approach, incapable of handling any ambiguity as in the frame/Bayes/MDP based approaches, and insufficiency in dealing with uncertainties as in the POMDP-based approach [6] [7] [38]. To overcome the shortcomings while retaining the advantages of the modified POMDP-based approaches, this investigation helps to improve the intention discovery by adding emotions into the user observation (O) in the POMDP tuple(S, A, O, T, Z, R, γ).
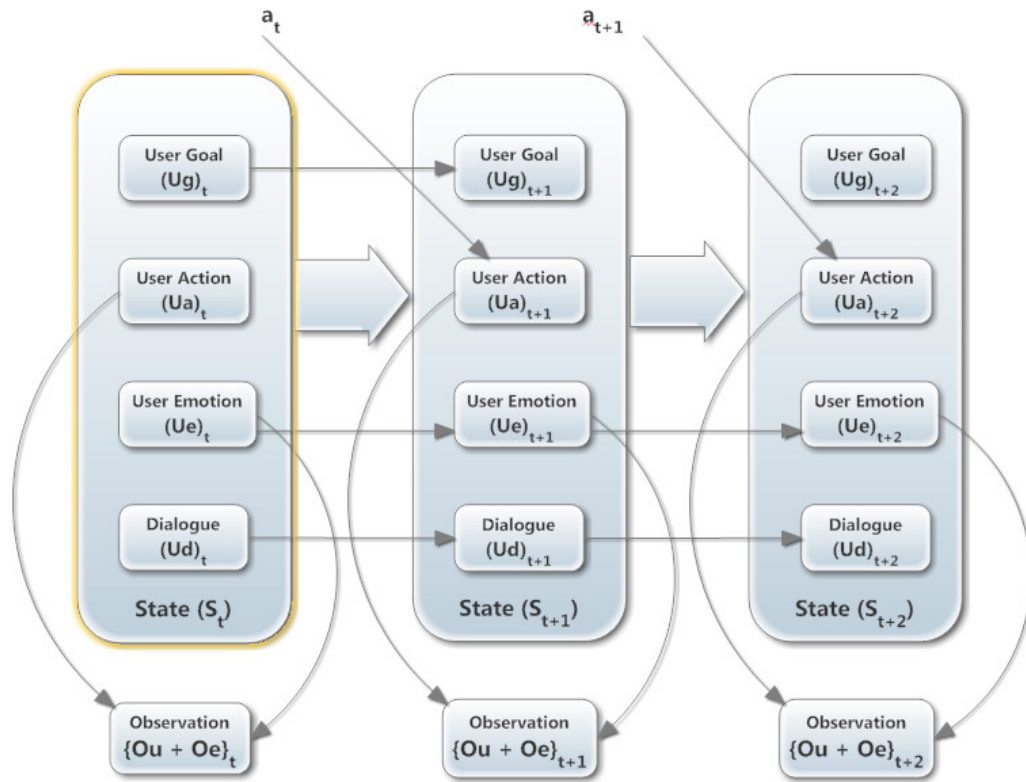
Figure 4.2.1.1: Proposed POMDP Transition method with emotions as Observation

The above state transition diagram explains the proposed dialogue model where the current POMDP approach has been extended with an impact of emotional component in it. Thereby, the State S is distributed into following four attributes: *User Goal, User Action, User Emotion* and *Dialogue State*. Thus an observation of the agent not only has the user action but also the emotional factor which helps improving the user intention prediction in the POMDP belief state analyser. As well, it is obvious that the user's action at every timestamp depends on system's action at the current timestamp, goals and emotions from the previous timestamp.
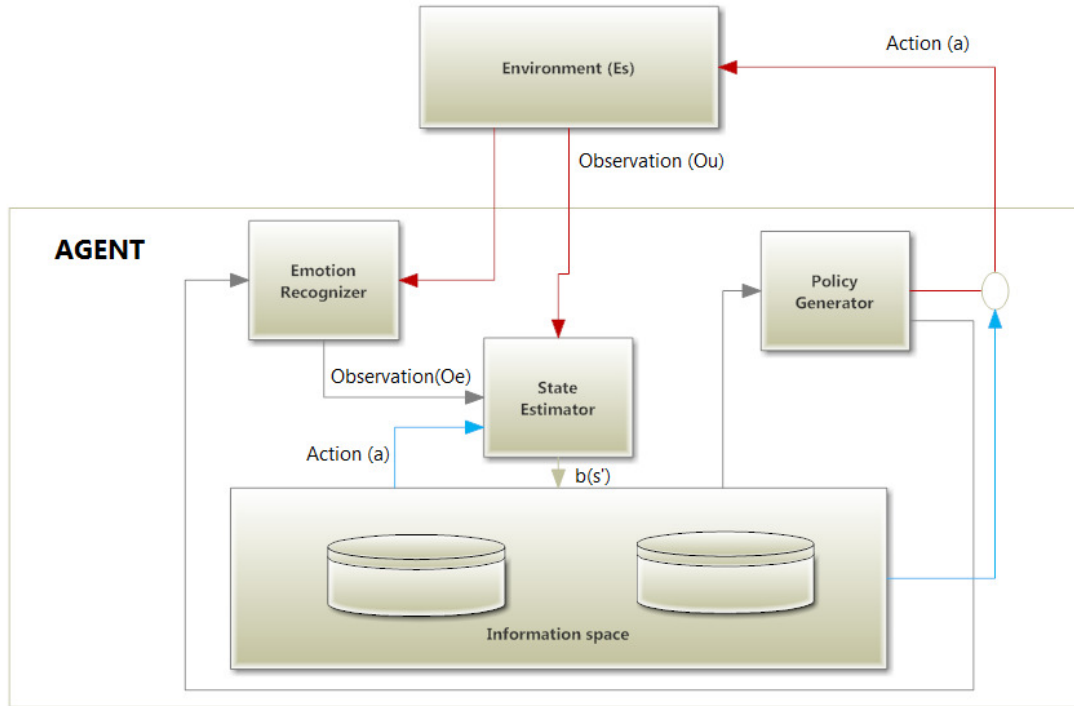
37

Figure 4.2.1.2 Proposed Architecture

Shown in Figure 4.2.1.2 is the architecture of the modified POMDP-based dialogue management in which the additional component interrupts the direct flow from b to policy (π). As a realization of the new planning strategy, the new policy is illustrated in the following equation.

$$\Pi_{new}:\ I_{k-1} \cup I_kn \rightarrow U$$

Action 'a' alters the original action when there is an unexpected change from I_{k-1} to I_k, or more accurately from the previous belief state to the current state. The added component also skips the original planner π and makes direct contact with the user. Therefore, the two main aspects of this architecture are the emotion recognizer and giving it as an input to the state estimator in the dialogue manager. We would like to explain the

emotion recognition process from textual and speech based data in the next sub-chapters and then would continue on how it infers the data into the dialogue model.

4.3 Emotion Recognition using Customized Decision Tree

In this section, it is explained in detail about how different classification techniques are used to predict the unknown user emotion using the given sets of data from the database and comparison of the same is also produced. The datasets are prepared to have more information to train the machine with different features about the data. Therefore this whole process contains three different steps namely: data import, feature extraction and addition (translate) and recognition. Before explaining Customized Decision Tree (CDT) it would be essential to understand the classical decision tree model [1].

4.3.1 Introduction to Decision Tree Model

The resource taken from North Western University [40] explains the decision tree in detail, which describes decision tree with the game 5-coin puzzle and explicitly shows the game trees associated. The diagram below explains the decision tree for the game of 5-coin puzzle:
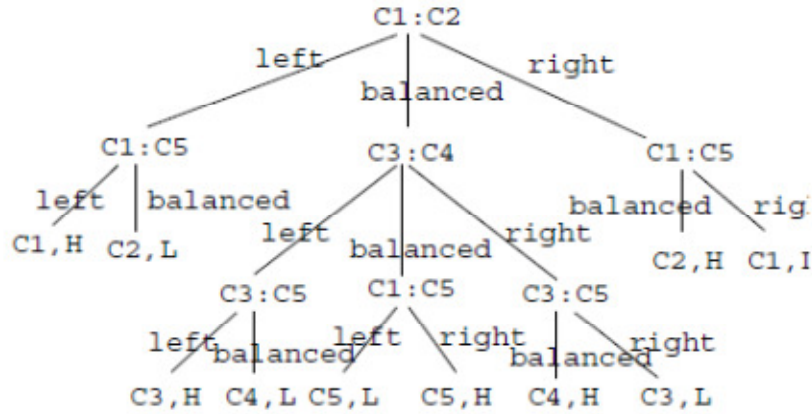
Figure 4.3.1.1: Decision Tree for the 5-coin Puzzle [40]

The Five-Coins Puzzle: In this puzzle we have five coins $C1, C2, C3, C4, C5$ that are identical in appearance, but one is either heavier or lighter that the others. The problem is to identify the bad coin and determine whether it is lighter or heavier using only a pan balance and comparing the weights of two piles of coins. The following discussion describes a solution to this problem.

First we compare the weights of $C1$ and $C2$. If $C1$ is heavier than $C2$ then we know that either $C1$ is the bad coin and is heavier, or $C2$ is the bad coin and it is lighter. By comparing $C1$ with any of the other coins, e.g. $C5$, we can determine whether the bad coin is $C1$ and is heavier (if $C1$ it is heavier than $C5$) or it is $C2$ and is lighter (if $C1$ has the same weight as $C5$). If $C1$ is lighter than $C2$ we proceed as before with "heavier" and "lighter" reversed. If $C1$ and $C2$ have the same weight we can try comparing $C3$ and $C4$ in a similar manner. If their weights are the same then we know that the bad coin is $C5$, and we can determine whether it is heavier or lighter by comparing it with $C1$. In each vertex of Figure 4.3.1.1 "$Ci : Cj$" means that we compare coins Ci and Cj by placing Ci on the left pan and Cj on the right pan of the balance, and each edge is labelled depending

on what side of the balance is heavier. The terminal vertices are labelled with the bad coin and whether it is heavier (H) or lighter (L). The decision tree is optimal in the sense that in the worst case it uses three weightings, and there is no way to solve the problem with less than that—with two weightings we can get at most nine possible outcomes, which are insufficient to distinguish among ten combinations of 5 possible bad coins with the bad coin being heavier or lighter.

4.3.2 Customized Decision Tree Algorithm

A decision tree is a hierarchy based classifier in which each branch node represents an option between a number of alternatives, and each leaf node represents a decision [41]. The general algorithm for decision tree is as simple as a nested if-then-else structure. There are nine features used in this study of emotion recognition, namely strength of angry, strength of sad, strength of surprise, strength of fear, strength of disgust, strength of joy, intensity of emotion, positive and negative sentimental strength [1]. The proposed approach evaluates the RMS (Root Mean Square) and mean of each dimension in an emotion class first. We use RMS along with the arithmetic mean because it is useful when the emotion database has both positive and negative values.
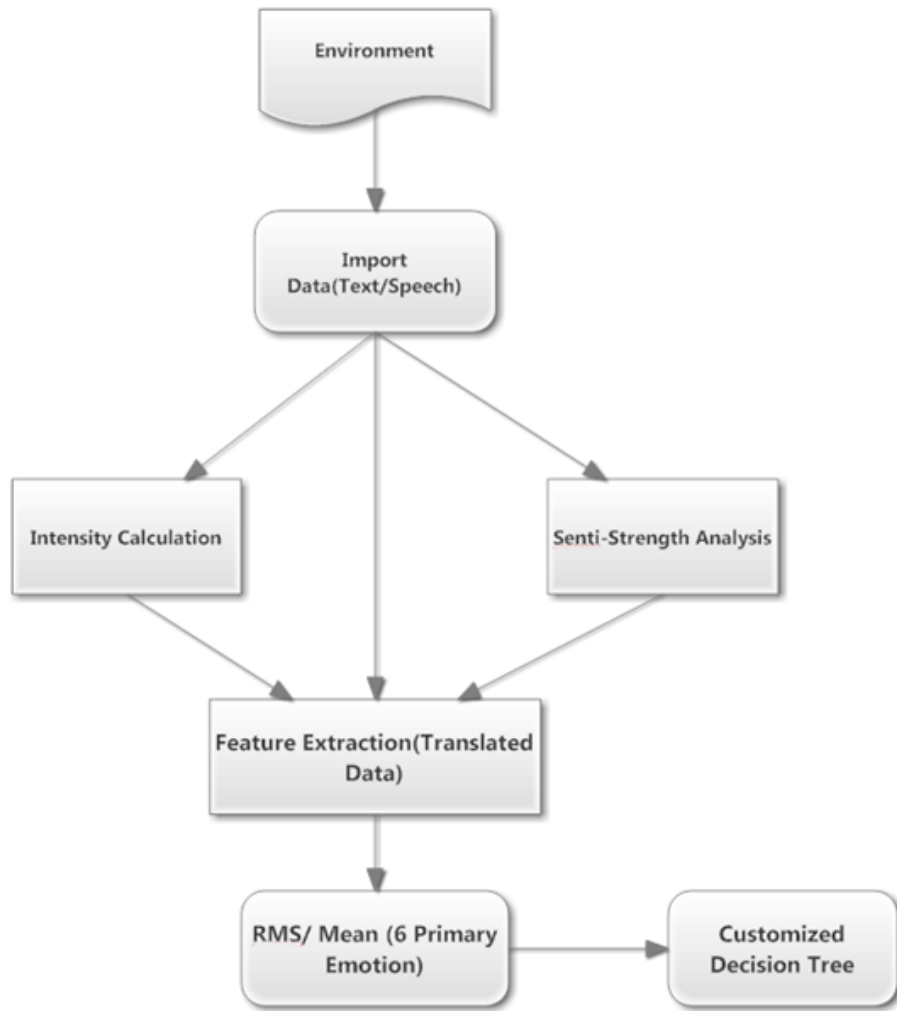
Figure 4.3.2.1 Overall Emotion Recognition Process [1]

The above diagram explains the overall architecture of emotion recognition process, where the necessary steps that have to be explained are namely, intensity calculation, senti-strength analysis and feature extraction module.

4.3.3 Intensity Calculation

The intensity that is evaluated in this investigation is nothing but the cognitive intensity of the user. It can be detailed as facets of thinking and dealing out information used in problem solving. The emotion texts are collected from known sets of data for evaluating the intensity. The details about the datasets that are used to train the system are explained in Section 5.1.1. Intensity of the emotion is analyzed with the formula as follows:

$$\text{Intensity(Iem)} = \frac{\text{Number of emotion keywords in the particular statement (Nkey)}}{\text{Total number of words in the statement (Ntotal)}}$$

Intensity of the emotion is calculated and updated in the database. This gives more information about the data for the machine to learn so that the efficiency of the learning should increase gradually.

4.3.4 Senti-Strengh Analysis

Positive and negative emotion strengths are updated to the database using the senti-strength software analysis. Senti-strength is a sentiment analysis (opinion mining) program designed to measure the *strength* of positive and negative sentiments in *short texts*, in which the language can be informal [42]. Fed with a set of short texts, it will allocate negative sentiment strength of -1 (least negative) to -5 (extremely negative) and positive sentiment strength of 1 (least positive) to 5 (extremely positive) to each one. Senti-strength is configured to analyze English language and is optimized for MySpace comments but can be modified for other languages and contexts by changing its configuration files. It should work reasonably well on any short English texts (i.e., a few

43

sentences each) [1] [42]. Section 4.3.5.1 shows the emotional strength updated from this interface.

4.3.5 Algorithm

As stated earlier, a decision tree is a hierarchy based classifier in which each branch node corresponds to an option from a number of alternatives, and each leaf node represents a decision [41]. In this approach, first the RMS and the mean of each dimension in the emotion class are calculated. There are seven features used in this emotion study. These features structures the necessary dataset for the emotion recognition and are namely: strength of anger, strength of joy, strength of sad, strength of fear, strength of disgust, strength, strength of surprise and intensity of emotion.

For every feature which is represented by each column in the dataset, the value of mean and RMS are calculated. This will construct the Mean-RMS dataset with seven emotional strengths and intensity.

$$\text{Mean} = \frac{\text{Sum of all values under the dimension}}{\text{Total number of values}}$$

Thus the mean is calculated for every dimension and recorded. Secondly, for every dimension the average influence that can be evolved by every datum with respect to a given dimension can be calculated by finding the root mean square value for each dimension in both the classes. The RMS of a collection of n values $\{x_1, x_2, x_3 \dots x_n\}$ is x_{rms}.

$$x_{\text{rms}} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2} = \sqrt{\frac{x_1^2 + x_2^2 + \cdots + x_n^2}{n}}$$

Using the above formulae the RMS of each dimension under it is calculated, globally for all seven features. In this approach the whole dataset of 1000x7 is reduced to just two sets of arrays i.e. a mean array (mean [7] [7]) and RMS array (RMS [7] [7]) where the first dimension denotes emotion and the second dimension denotes the number of dimensions which is seven. The algorithm uses these two arrays as a metric in predicting the unknown classes of mixed dataset, then for each test data finds the distance metric of the dimensions with RMS[1][7], mean[1][7] and RMS[2][7], mean[2][7].

4.3.5.1 Emotion Strength Update

The emotion strength is updated for every feature in the Mean-RMS dataset. Positive and negative emotions are not used in the Mean-RMS calculation. Instead, the emotion strength is updated directly using the following customized rule.

Negative rule	Positive rule	Possible emotions
$S_- = -1$	$S_+ = 2$	Joy, surprise
$S_- = -1$	$S_+ > 2$	Joy, Surprise
$S_- + S_+ = 0$		Do Nothing
$S_- = -2$	$S_+ = 1$	Sad, disgust
$S_- = -3$	$S_+ < 3$	Sad, Fear
$S_- = -4$	$S_+ = 4$	Sad, Fear, angry
$S_- = -5$	$S_+ = 3$	Angry, Sad, Fear

Table 4.3.5.1: Possible Emotions Prediction Table [1]

45

The possible emotions with the value of positive strength and negative strength can be predicted. Based on the definition of the emotion strength the rules are framed to calculate the possible emotions and to update the points for a particular emotion observed in the statement.

4.3.5.2 Homogeneity Problem

The problem of homogeneity arises in the procedure of finding the emotion from the Mean-RMS dataset. This could be solved by finding the Euclidean distance measure between the unknown data and Mean-RMS value of each emotion. Table 4.3.5.2.1 explains this algorithm clearly with the entropy values for the datasets. The distance measure (DM) or the Euclidean distance is calculated between only two different emotion sets at a particular time. We calculate the entropy measure 'p1' and 'p2' for the two compared emotions if there is a heterogeneity condition.

INPUT: {DM_rms1, DM_rms2, DM_mean1, DM_mean2}

OUTPUT : {*Emotion*()}

BEGIN:

If ((DM_rms1<DM_rms2) AND (DM_mean1<DMs_mean2)) then

   Test data = > emotion A

Else if ((DM_rms1>DM_rms2) AND (DM_mean1>DM_mean2)) then

   Test data => emotion B

Else if (none of the above satisfies) then

 // here the homogeneity is not there with the adjacent condition

 // hence calculating the Entropy Measure similar to the classical method

p1 = ((-1)*DM_rms1*(log (DM_rms1)/log (2)))-(DM_mean1*(log (DM_mean1)/log (2)));

p2 = ((-1)*DM_rms2*(log (DM_rms2)/log (2)))-(DM_mean2*(log (DM_mean2)/log (2)));

If (p1<p2) then   // p1 and p2 are the two entropy measures

   Test data => emotion A

Else

   Test data => emotion B

End If

Table 4.3.5.2.1: CDT Homogeneity Algorithm

Hence by using the above algorithm, the emotion classes of the test dataset can be evaluated and the results of which are discussed in the later part. The algorithm looks very simple and less complex in structure and thus the question arises whether this transformation is suitable for this whole huge dataset. The question can be answered only

47

by pure experimentation and testing by giving the known trained data as an input and make the model to predict the same.

4.4 Inducing Emotions to Modified POMDP

Unlike previous POMDP approaches our method provides the services considering all factors from the perspective of the user including his/her emotions. This is to achieve the optimal goal with few dialogue states in shorter time. We have also concentrated more on pruning the number of dialogue states at least by ten percent depending upon the type of conversation in the domain. Our dialogue manager has the same components exactly like the previous dialogue managers composed of such knowledge base, updated dialogue history, discourse generator and session model.

The system starts with the greet message followed by the system query to request for what type service to be provided to the user. Initially, at time 't' the system is normally in some unobserved state, $s \; \varepsilon \; S$. When the conversation established between the user and the system, the dialogue state takes a transition from s to s' by the increment of time stamps. Choosing the necessary action for the dialogue in our system is dominated by the four control modes in our system. The decision making or the switch between the control modes depends on the time available to make decisions on the particular context of the dialogue. Hence we have introduced a factor *TA* which represents the available time for choosing the essential action which depends on the machine state s_m, set of observations o', machine actions a_m and the belief state $b(s)$ of the machine, as denoted by $TA(S_m, a_m, o', b)$ at each time *t*. Depending upon the values of TA, and the machine states s_m the switching between the modes takes place, which does not mean that the decision is taken

48

now. The decision making is done by comparing the state of the system s_m, machine actions a_m, observation o' which is in combination of user action and user emotion {Ua + Ue}, belief state b and the type of control mode TA at present the dialogue is in (i.e. at time t). To calculate the belief distribution of the dialogue, we have also introduced a factor t_r which represents the response time of the system to the user in milliseconds. Hence the belief state distribution is updated based on o' and action a as follows:

$$B'(S') = \frac{\sum_{s \, \varepsilon \, S} b(s)T(s,a,s')O(a,s',z)t_r(s)}{O(a,s',z)}$$

Here, the dialogue states and actions represent the machine states and machine actions respectively. And the value of TA depends on the current action and belief state distribution, which is given by TA(O'(u + e) | s, a, b'). Based on the current belief state and available time, the machine selects an action $a \, \varepsilon \, A$, receives a reward r(s_m, a_m) and transitions to a new unobserved state s'. Then, the system receives an observation o' ε O depends on the system state s_m and the system action a_m. Finally, the belief state is updated with a new one at particular time t.

4.4.1 Rewards

We have also changed the reward model depending upon the modified POMDP approach with four control modes. Previous POMDP model has two types of reward with some positive values for correct dialogue, i.e., the system exactly understand the user utterances and provides exactly the service as what the user wants. Negative values or

zero stands for incorrect dialogue in which the system does not understand the user utterances exactly. In our approach, we have represented the rewards type depending upon the control modes: +100 if the dialogue state is in strategic mode and tactical mode as the system understands what the user wants, or -100 if the dialogue is in opportunistic mode as the user does not provide correct information or if there any conflict in the information provided by the user. Here, the system receives a negative reward and an instruction to provide options to the user. A zero reward means the system is in the scrambled mode because, in this mode, the system does not receive any proper information or query from the user but some disturbances, error or some corrupted information. λ is used as discount factor at time t, and the reward R is given by,

$$R = \sum_{t=0}^{\infty} \lambda^t r(b_t, a_m, t_r) \ \sum_{t=0}^{\infty} \lambda^t \sum_{s\,\varepsilon\,S} b_t(s) t_r(s)\, r(s, a_m, t)$$

Each action is determined by a policy π and POMDP system involves in finding the optimal policy π * for the application which maximizes the rewards.

$$\pi^*(s_t) = a[argmax_{a\varepsilon A}(b_t, t_r)]$$

4.4.2 Confidence Score Evaluation

We have also incorporated the confidence score by providing an estimation of real value to show how exactly the system understands the user utterances as denoted by *c* with a predefined threshold value 0, which in turn affects the rewards received for each dialogue state. We have not made any changes to the confidence buckets as it depends on

50

the user's utterances and system's observation of user action a_u. We have used the same evaluation for calculating confidence score as it does not make any change in choosing system actions. But we have included an option of paraphrasing or double checking mechanism to increase the confidence scores. In this case, the system transitions to tactical mode because the system reconfirms the user utterance by providing an option in order to understand the user requirement exactly and reach the optimal goal within the available time. A graphical flowchart representation of our proposed work and its pseudo code are given as follows.
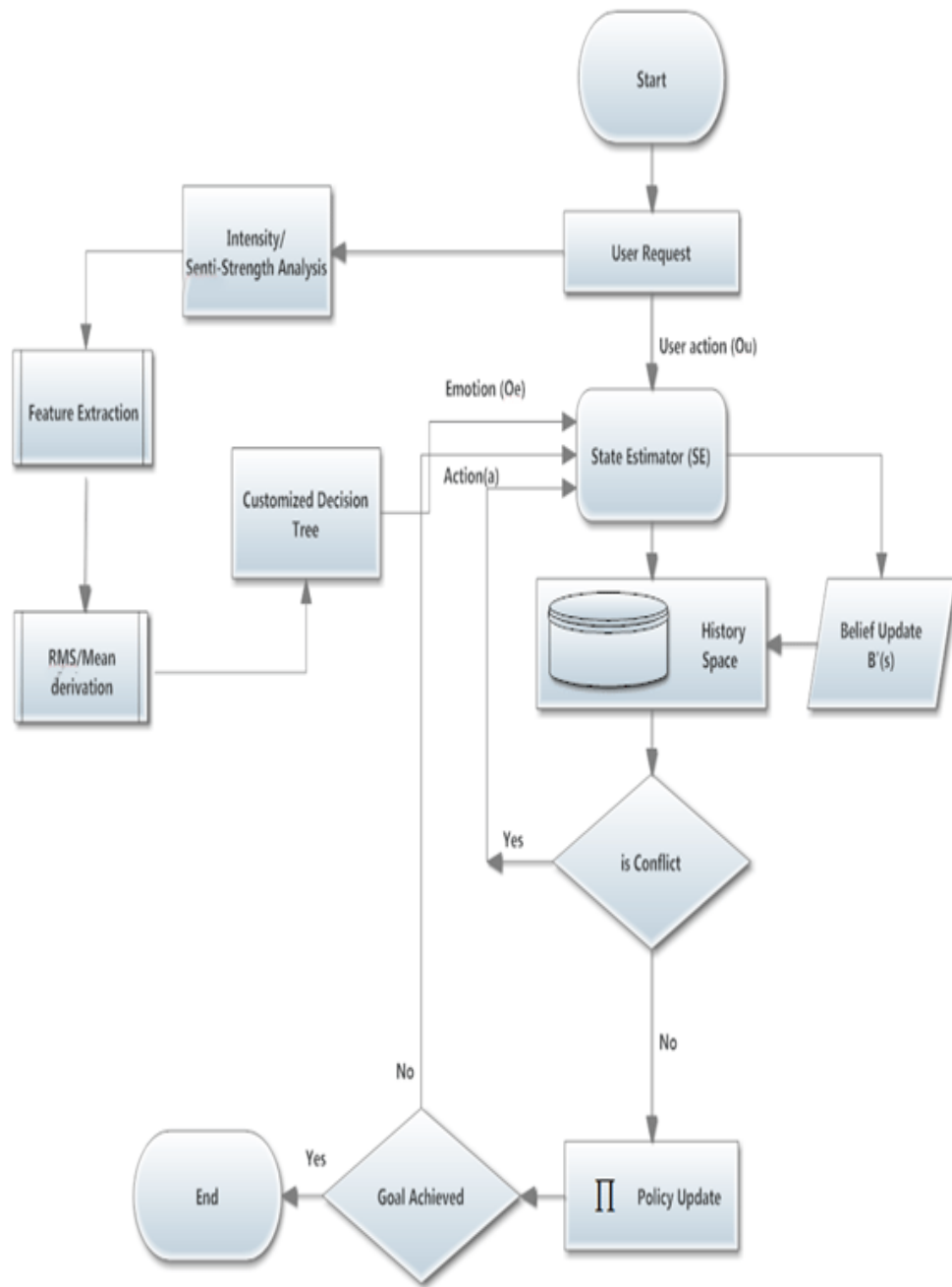
Figure 4.4.2.1: Flow Chart Representation of Proposed Work

EMPOMDP *(bel(s), o_u, o_e, a):*

INPUT: {Belief State (s), Observation list (User Action, User Emotion, User Goal),

action (a)}

OUTPUT: {s', Belief State'(s'), Scenario (S)}

CURRENT_BELIEF:= bel (s)

For all States (s) do

    Bel'(s') = α P((o_u + o_e)$_{t+1}$ | s_{t+1}, a_t) $s \, \mathcal{E} \, S \sum_{i=0}^{t}$ P(s_{i+1} | s_i, a_i, O^e_i) $b_i(s)$

    If (Bel'(s') < 0.05) then

    {Ignore state of belief}

    Else {

        SCN: = Generate Scenario (Bel'(s), Bel(s))

        Domain_Constrain_validation (Bel'(s))

        If (! VALIDATION.FAIL) && (SCN.Equals (USER.GOAL)){

            Machine action = OUT.POLICY (Bel'(s))

            Return (s', Bel'(s'), SCN)

        }

        Else {

Machinenext_action= *a* with the hint

        Bel'(s) = CURRENT_BELIEF

        return Machin_next_action

        }

End For

Figure 4.4.2.2: Pseudo Code for New Approach

53

In the pseudo code of Figure 4.4.2.2, the *Bel(s),* Oe, Ou and *a* are the inputs of the proposed method. *Bel(s)* is the previous belief state of the last stage, o is the up-to-date observation and *a* is the last action taken by the machine. By recording the previous belief state, the belief state will be updated based on the POMDP theory and for all the belief states with possibility less than 0.05. For all the rest of the belief states, the domain constraint validation process function *DomainConstrain.validation()* will be invoked to check the conflicts of the belief states. The failure validation will result in the action to require further information with hints and the roll back of the belief states. Otherwise the action produced by the original POMDP solution policy *out.policy (Bel'(s))* will be taken.

4.5 Conclusion

In this chapter, we have discussed about the contributions made in the POMDP based dialogue management systems to make dynamic decision making depending on the control modes of the approach with respect to observation, emotions and current state of belief. We have also presented the modified approach of POMDP for handling real world state and improbability. As well, we have discussed how our approach extends the reward model and confidence scores. The main advantage of our proposed model is the robustness compared to the different dialogue management approaches.

CHAPTER V

EXPERIMENTATION AND RESULTS

This chapter will review the effectiveness and efficiency of the proposed system. The experimental analysis has been subdivided in two sections. The beginning of this chapter will discuss about the qualitative analysis in detail carried out between the proposed system and some of the benchmarks and the baselines. The order of further explanation here are as follows: The domain background applied in our case study will be introduced first and the implementation platform, utilized tools and corresponding details will be explained after. The results for the emotion recognition process are also explained to understand the efficient emotion induction to the POMDP model. Finally, the results under different possible scenarios, analysis of the outcome and comparison with the baselines will be given.

5.1 Implementation Setup for Emotion Recognition

In this section the detailed implementation and experimentation results of the classification of emotions are discussed, analyzed and the resutls are shown. As per our earlier discussion there are four main implementation required for this anaylsis:

- ✓ Intensity Evaluation
- ✓ Senti-Strength Analysis
- ✓ Secondary Dataset Preparation
- ✓ Emotion Recognition using Customized Decision Tree (CDT)

55

5.1.1 Intensity Evaluation

Intensity of the emotion is calculated and updated in the dataset. This gives more information about the data for the machine to learn so that the efficiency of the learning is expected to increase. Two datasets from digg website [42] and SemEval Affective Text 2007 [43] are studied. The emotion texts are collected from both the datasets. Intensity of the emotion is analyzed with an interface as follows:
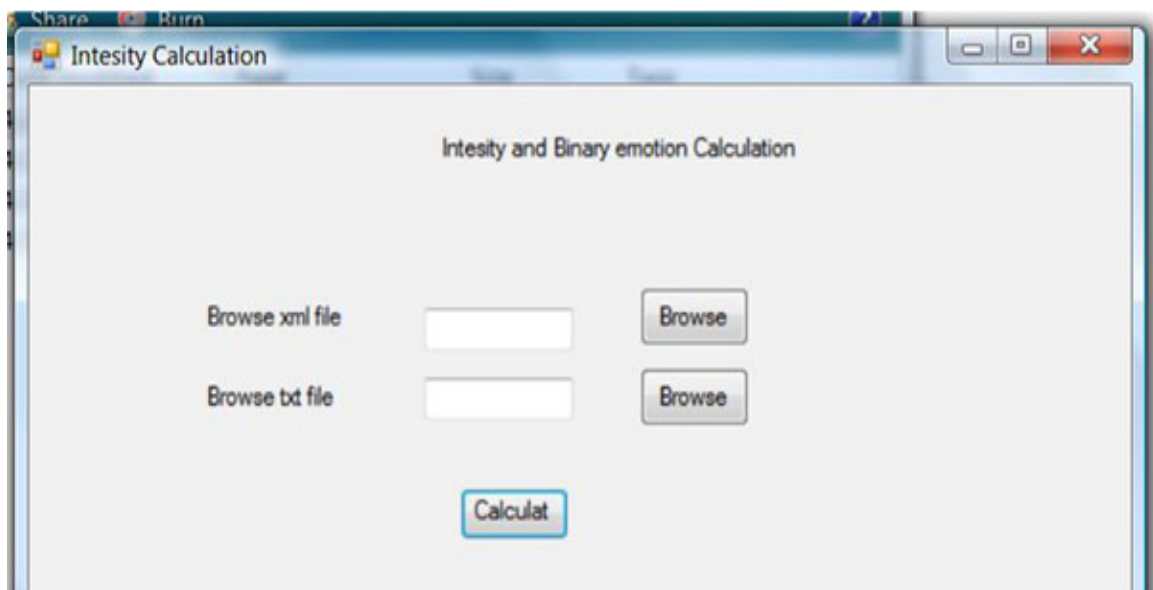
Figure 5.1.1.1: Intensity and Binary Emotion Calculation

The above is a C# application which calculates the values either from an XML/Text inputs as it has to take care of Textual or Speech grid inputs. The intensity of texts for example deals with keywords, emoticons, boldness of the letters and cases of the text sense. These values are scaled initially from 1 to 5 which sense lower to a higher emotional intensity as shown in Figure 5.1.1.2. It does not necessarily have to have fixed intervals for six primary emotions as intensity can be lower to higher levels for each of

56

them individually. When the intensity value is higher, the prediction of emotion becomes better. The results for this evaluation are given after discussing the other parts.

Data 1	Data 2	Data 3	Data 4
2.028	2.374	2.06	2.371
2.05	2.349	2.077	2.422
2.029	2.336	2.077	2.422
2.03	2.338	2.082	2.383
2.036	2.346	2.059	2.399
2.078	2.388	2.091	2.402
2.036	2.328	2.098	2.409

Table 5.1.1.2: Intensity Values Metric (Partial) [1]

5.1.2 Senti-Strength Analysis

Reiterating the earlier statement, positive and negative emotion strengths are updated to the database by the senti-strength software analyzer. For each text, the senti-strength output is two integers: 1 to 5 for positive sentiment strength and a split score of -1 to -5 for negative sentiment strength. Here, 1 or -1 signifies least sentiment and 5 or -5 signify strong sentiment of each type. For example, a text with a score of [3, -5] would include moderate positive sentiment and strong negative sentiment. A neutral text would be inferred as [1, - 1]. Two scales are used because even short texts can enclose both positivity and negativity. The objective is to perceive the sentiment expressed rather than its overall polarity [42].

57

Figure 5.1.2.2 and Figure 5.1.2.3 show the implementation setup of the senti-strength analysis.
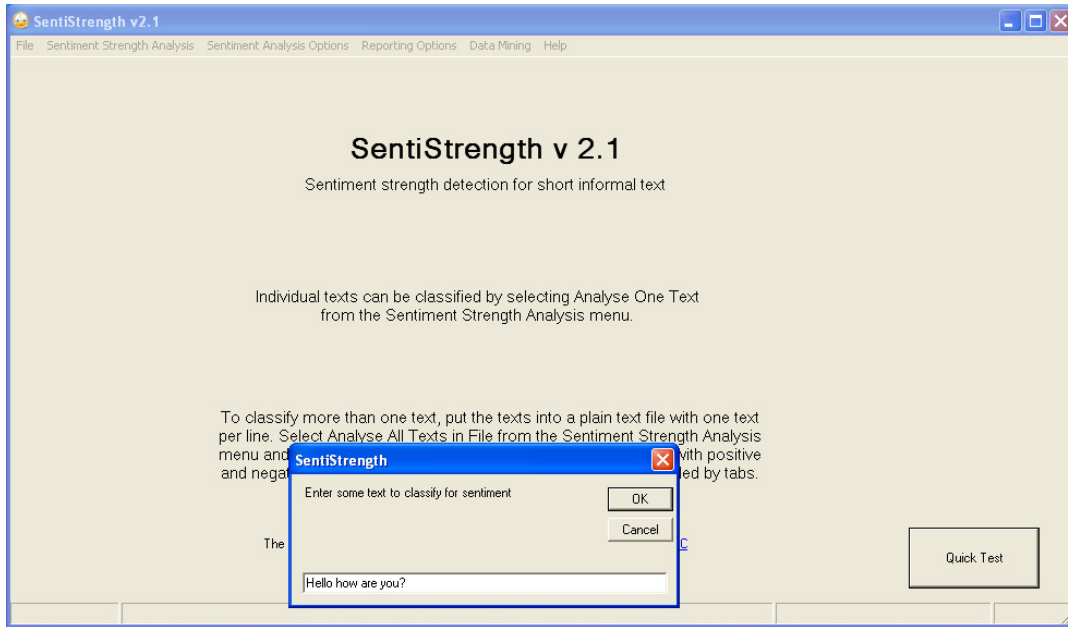
Figure 5.1.2.1: Text Input to Senti-Strength [42]

Figure 5.1.2.2: Text Input to Senti-Strength

Figure 5.1.2.3: Positive and Negative Strength Output

5.1.3 Secondary Emotional Dataset

The datasets used in this project have seven columns with different emotional strengths for a sentence and the intensity value. The emotional strengths are such as strength of angry, strength of surprise, strength of sadness, strength of fear, strength of disgust, strength of joy. These seven columns make the decision for a particular statement's emotion. They are as well the key elements or the attributes in determining textual emotions and hence can be called as features hereafter. Strength of emotions in the training set is done by human annotators. The primary datasets are obtained from two sources: SemEval-2007 Task 14: Affective Text [43] and Cyber emotions [42]. The secondary dataset for analysis is obtained with the combination of the features used in the emotion classification dataset and intensity as follows:
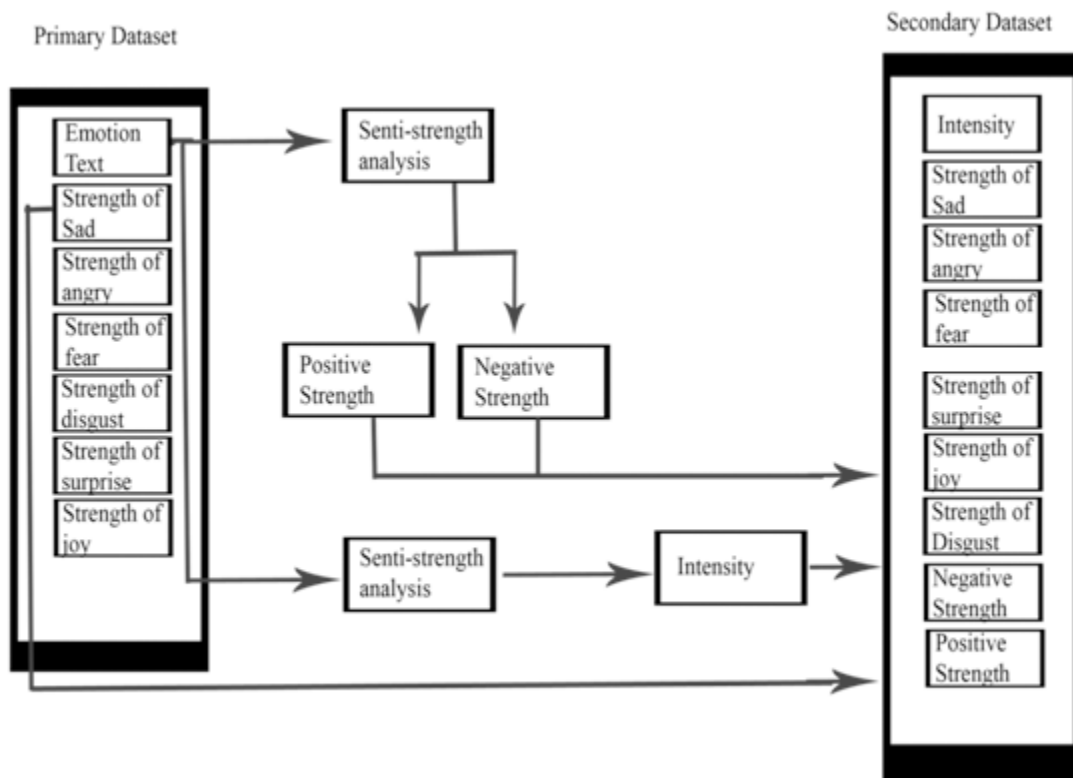
Figure 5.1.3.1: Secondary Dataset Generation

The secondary dataset is used for experimentation of the text emotion analysis. The emotional intensity calculation and experimentation are done using C# application. Datasets are structured with necessary features using Kettle software [44] as shown in Figure 5.1.3.2.
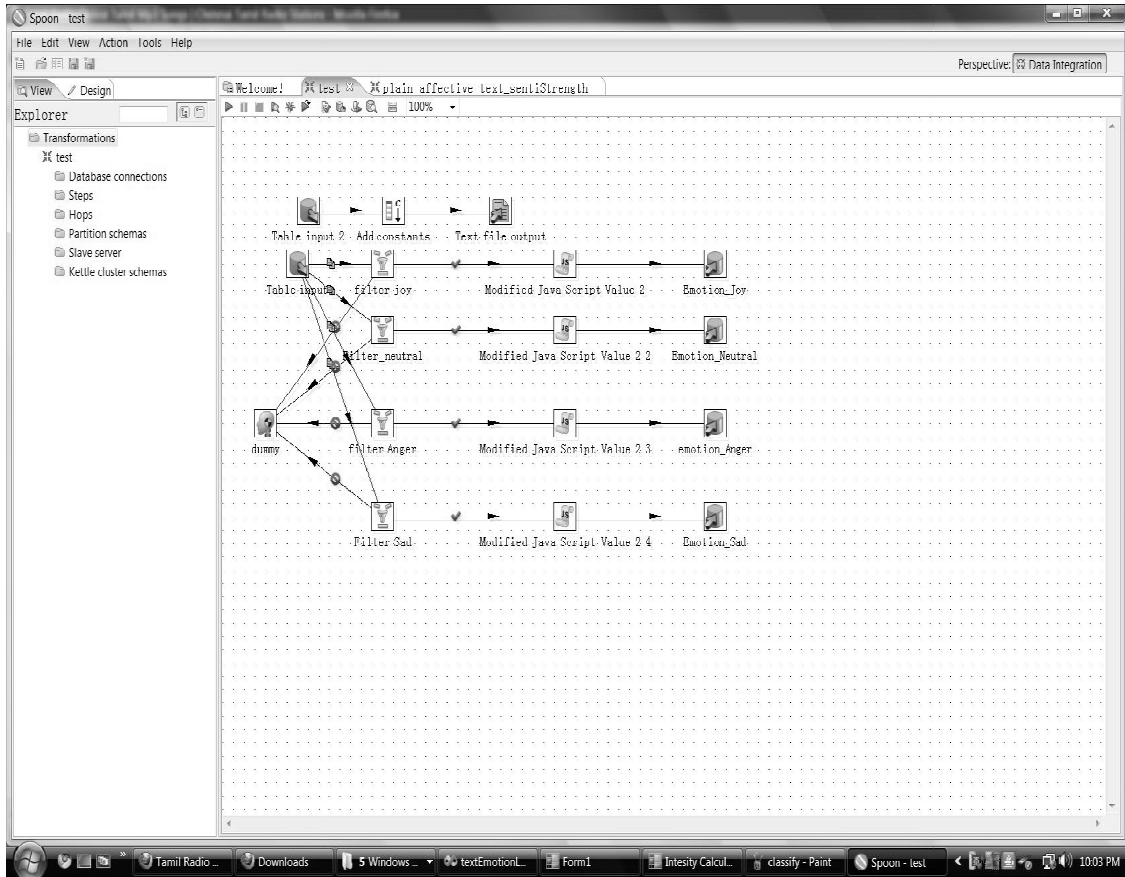
Figure 5.1.3.2: Extraction of Data from two Different Sources

5.1.4 Customized Decision Tree Implementation

The implementation of the customized decision tree classifier has to evaluate the overall mean and RMS values of seven features namely: Anger, Disgust, Fear, Joy, Sad, Surprise and Intensity. This is done in Visual studio C# .Net and the graphical representation using the Microsoft Excel for comparison. After calculating the mean and the RMS values, the graphs were plotted between the seven classes to identify the difference maintained between each of those classes. There are 4 modules implemented for this experiment as follows:

1. Mean-RMS dataset generation

2. Finding the set of possible emotions.

3. Updating the emotion points.

4. Finalizing the emotion class.

The secondary dataset is derived from multiple datasets using the Senti-analysis and intensity calculation as described earlier in this thesis. This secondary dataset is used as the input to the C# implemented windows application as shown in Figure 5.1.4.1.
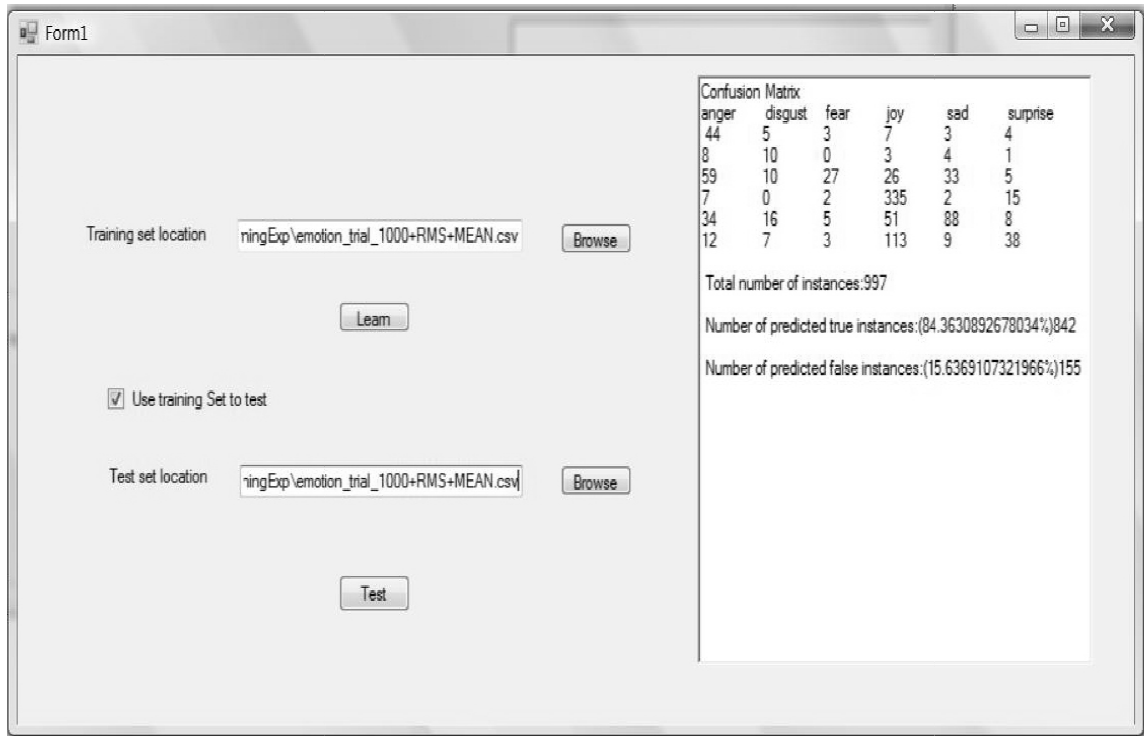
Figure 5.1.4.1: C# Application for Experimenting CDT

The implemented application uses an intermediate dataset to calculate the mean and the RMS for every feature in the secondary dataset. Let this intermediate dataset be referred as Mean-RMS Dataset which is used for the classification of emotion. Thus, after running the customized decision tree algorithm for evaluating the overall mean and the RMS values, the emotions are predicted in the mixed dataset. The Mean-RMS dataset is with 7 rows of mean and RMS. After learning the Mean-RMS dataset, the machine could then be able to classify the emotions from the test dataset. Test data is browsed with the windows application developed and then the test option is selected. This creates a new file with the predicted emotions in the last column of the Mean-RMS dataset.

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5.1.5 Customized Decision Tree Evaluation

The graphs below show the variation of RMS values of the emotion class dimensions. The dimensions are plotted along the 'x' axis as follows: strength of angry, strength of surprise, strength of sadness, strength of fear, strength of disgust, strength of joy and intensity of emotion. The mean, the RMS and respective random emotion data are plotted on the 'y' axis. The graphical pictures demonstrate that the difference between the two classes lies only in certain dimension values, which indicates that the classification process needs a better classifier to make the exact prediction. Hence it is evident that using any classification technique, it is practically impossible to provide 100% accuracy in predicting the emotional data.
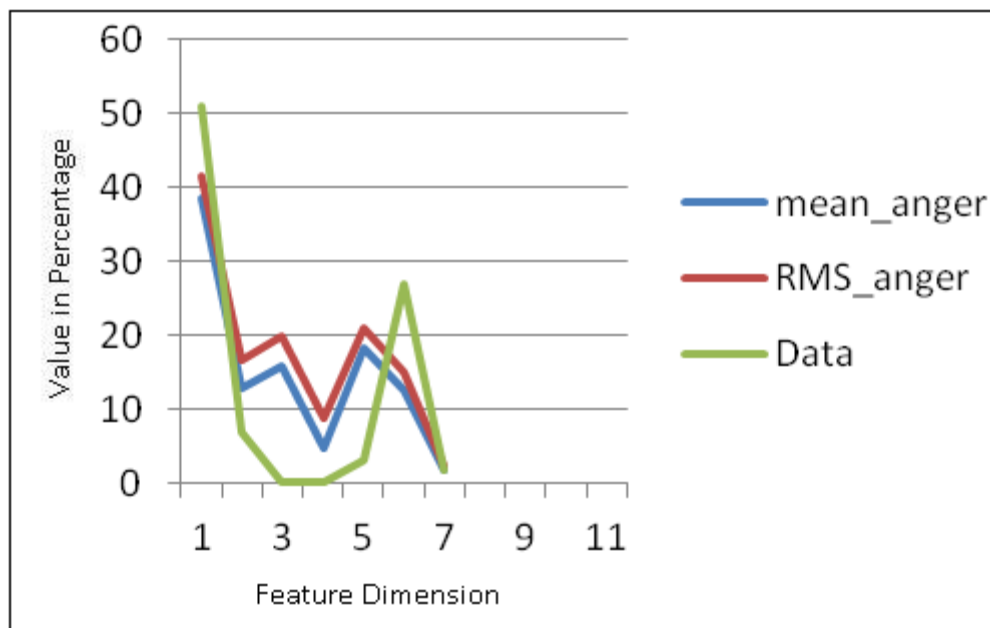
Figure 5.1.5.1: Anger Emotion Class with Mean and RMS
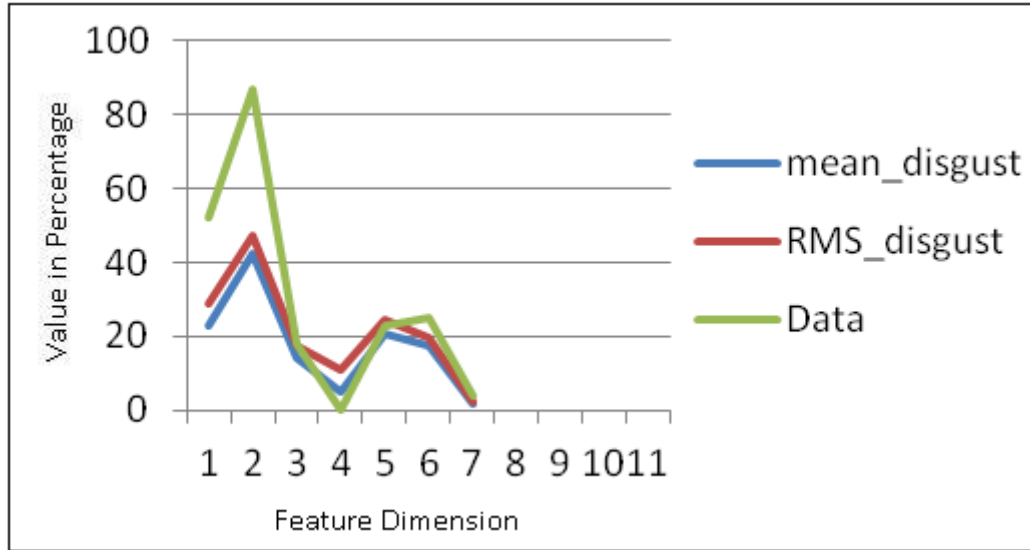
Figure 5.1.5.2: Disgust Emotion Class with Mean and RMS
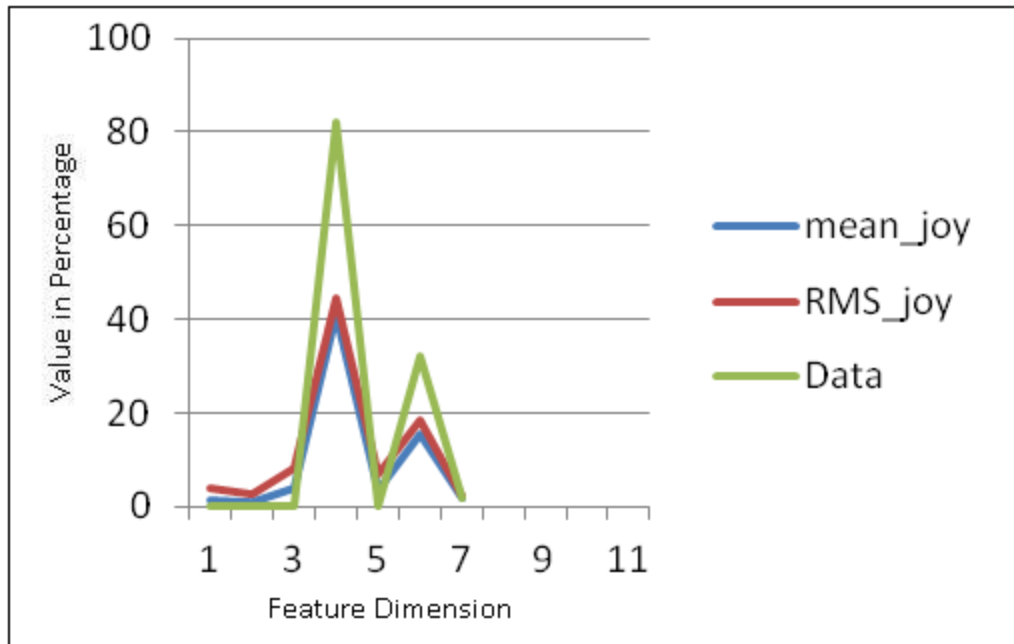
Figure 5.1.5.3: Joy Emotion Class with Mean and RMS

64
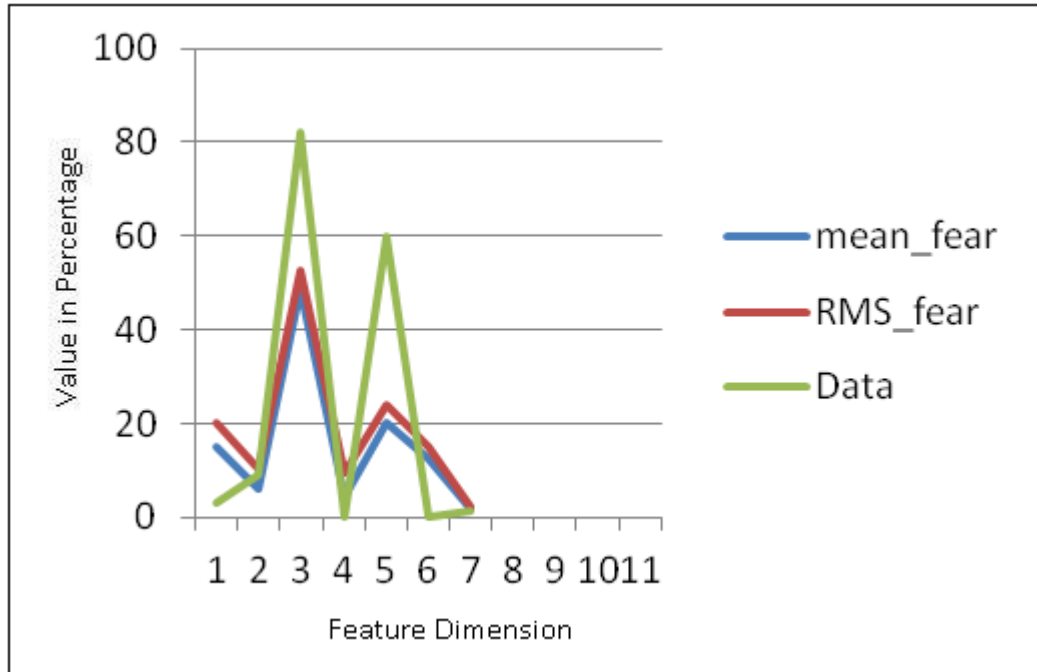
Figure 5.1.5.4: Fear Emotion Class with Mean and RMS

Consequently, running the customized decision tree algorithm after calculating the mean and the RMS values to predict the emotion class in the mixed dataset, it predicted 926/1005 in joy class, 630/996 surprise class, 661/928 sad class and 884/1042 anger. Fear class and disgust class have very small numbers in training so they cannot be taken into account for calculating the efficiency of the classifier. The above graphical results indicate that the classification works better with respect to the knowledge gained from the datasets. The prediction process could be improved by training the system with large feeds of known data or improving the classifier with further modifications, which are discussed in Section 5.3.

65

Mixed Data	Emotion	Occurrence	Homogeneity count	Entropy measures
Data1	Joy	5	0	
Data2	Disgust	4	1	p1=-185.8704 p2=-185.2176
Data3	Joy	6	1	
Data9	Joy	8	2	
Data10	Anger	4	0	
Data11	Sad	3	0	
Data12	Surprise	7	1	
Data13	Fear	11	0	

Table 5.1.5.5: Predicted Unknown Emotion (CDT)

5.1.6 Validation of Customized Decision Tree

The simple and easy way to validate the algorithm is to induce the known emotion dataset into the prediction model and calculate the accuracy using it. We can calculate 'True Positive' and 'False Positive' value and then build a matrix between the True positive ratio (TPR) and the random data. The machine is trained with close to 1000 data in each of the emotion set, and a dataset is prepared whose emotions are known and given for prediction. The final predicted emotion for every data is noted and validated with the originally obtained emotion. The implemented C# application has functionality of testing the algorithm with unknown emotion. The predicted emotions are verified with the emotion classified by an annotator. The validated result is represented in the form of confusion matrix with a small mixed set example of close to 900 mixed set of emotions.

66
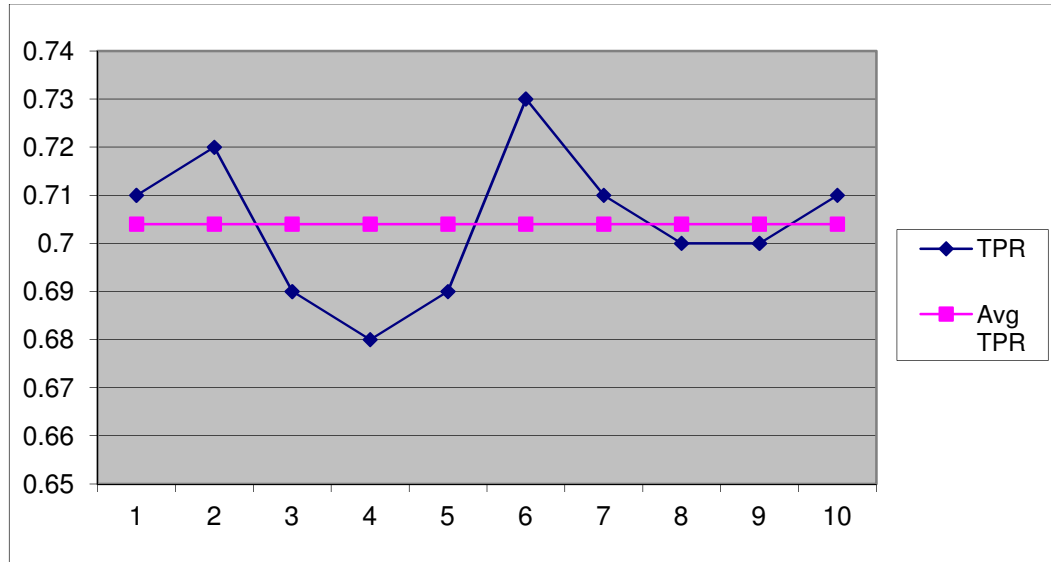
Figure 5.1.6.1: True Positive Ratio Graph for 10 Subsets of Training Sets
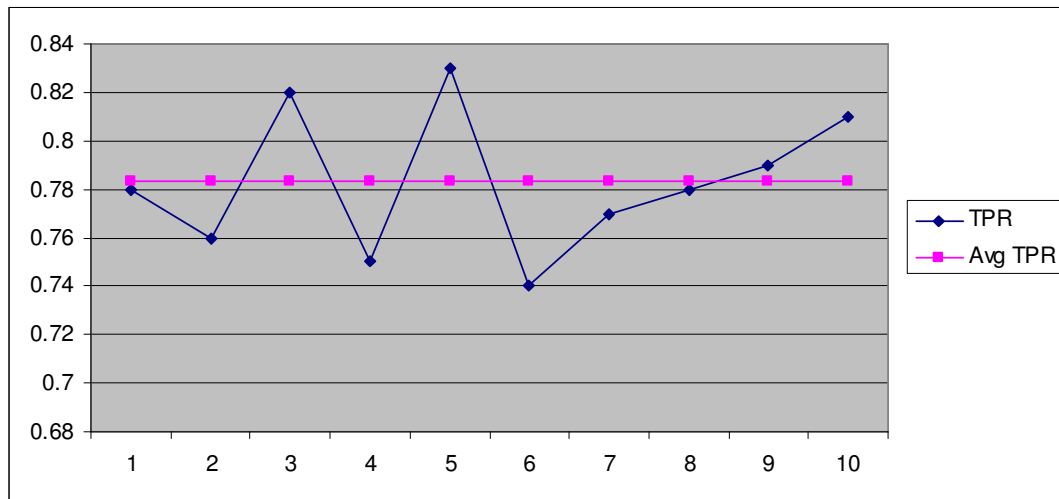
Figure 5.1.6.2: True Positive Ratio Graph for 10 Subsets of Test Sets

67

	anger	disgust	fear	joy	sad	surprise	Percentage
anger	48	5	3	7	3	4	72%
disgust	8	18	0	0	4	1	59%
fear	27	10	108	26	33	5	61%
joy	7	0	2	335	2	15	92%
sad	34	16	5	21	156	8	65%
surprise	12	7	3	38	9	131	65%

Table 5.1.6.3: Confusion Matrix on Test Set

5.1.7 Quantitative Analysis

The purpose of this pizza ordering system will be to provide a client service by considering the customer requirements and intentions. The creation of such a system with a 3D talking head driven by emotions will make it more engaging to the end user. This motivated us to create a system that combines the current state-of-the-art 3D facial animation with a spoken dialogue system, along with a new cognitive model for generating emotion of the user trying to interact and order the pizza. Thus the new algorithm was incorporated to find the user emotion after each transaction was completed. We achieved significant results to find the human emotions after ordering the pizza using this application.
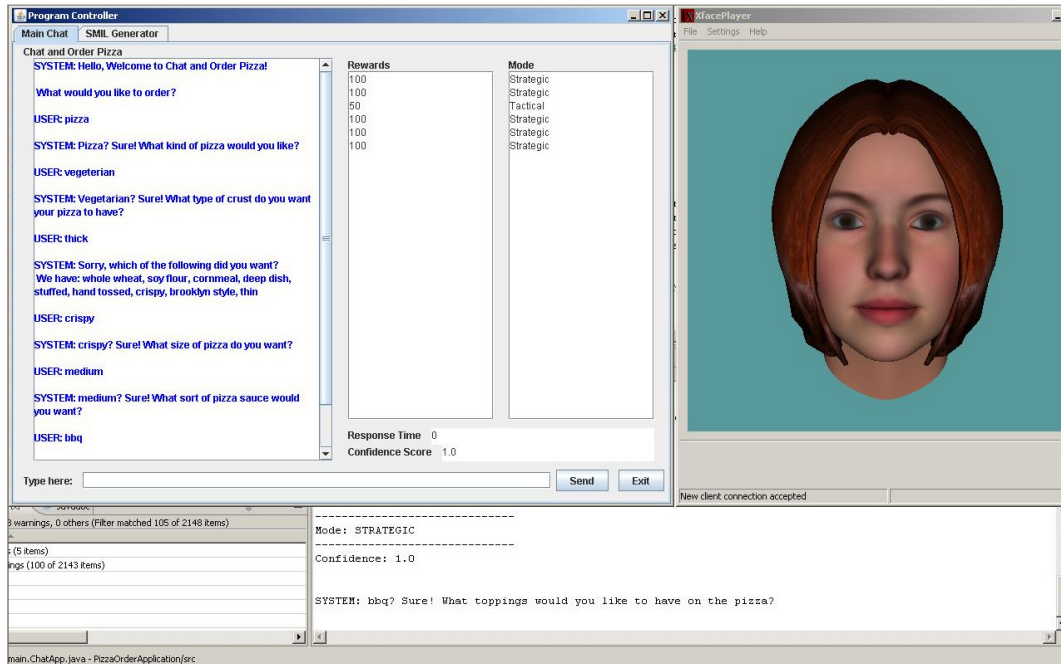
Figure 5.1.7.1: Pizza Order Application for Experimentation

We ran several possible test cases and ran the algorithm for the user inputs, which were able to deduce the emotions joy, anger and sadness, pretty easily with the sentences used by the user. Most of the test cases came to neutral emotion (no-emotion) as the user typed in only one sentence like "pizza" for the question "what would you like to order?" and "large" for the question "what size of a pizza would like?" The algorithm could construct more accurate emotion of the user, if there is enough information provided. For example, "I would like to order a pizza please" instead of just "pizza", in which case the overall emotion can be found more accurately by grading emotional scores and finding sentiment strengths of each conversation. The final results are published with the POMDP's results which would essentially make more sense.

5.2 Implementation of Modified POMDP with Emotions

Experiments are conducted based upon a simulated situation in which an agent provides assistance at a pizza restaurant to a human user for the purchase of a pizza. Hence, before we explain how we generate test samples for the Modified POMDP approach we would like to explain in detail about the user simulator. This user simulator system is implemented using JAVA under Eclipse Indigo and the knowledge base has been designed using MY SQL, In addition, a connection has been established between both front end and back end applications and data transfer (ETL) is done using Pentaho Data Integration Kettle [44].

We could easily call the user simulator as a POMDP mock up as it imitates all the necessary steps that a POMDP has to do, in order to create an absolute test set to test the new system and compare it with the benchmark.
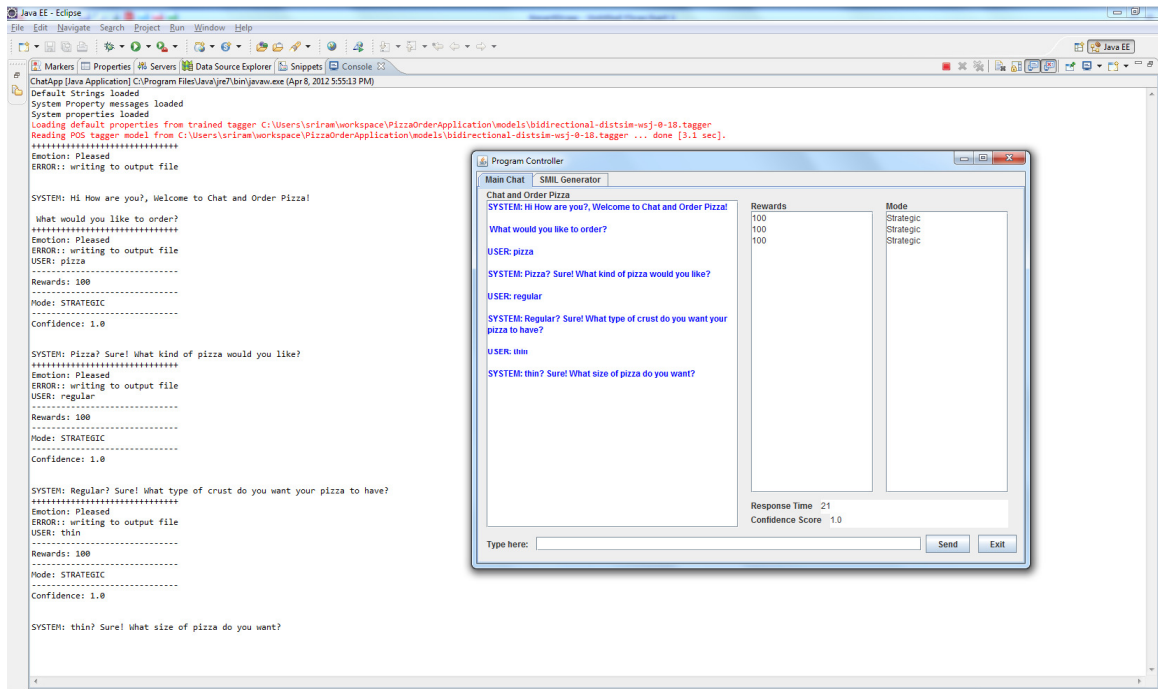
Figure 5.2.1: User Interface of User Simulator (POMDP Mock up)

In the user interface/chat screen, we have also displayed the emotion, rewards, mode of the dialogue and confidence scores just for our own tracking purpose to test whether the system performs efficiently. As we use the history space of the dialogue to make decisions or choose system actions, the developed dialogue mock up tracks the system actions, confidence scores, rewards, mode of the dialogue and transition between the modes, response time of the system for each of the dialogues and the belief states.
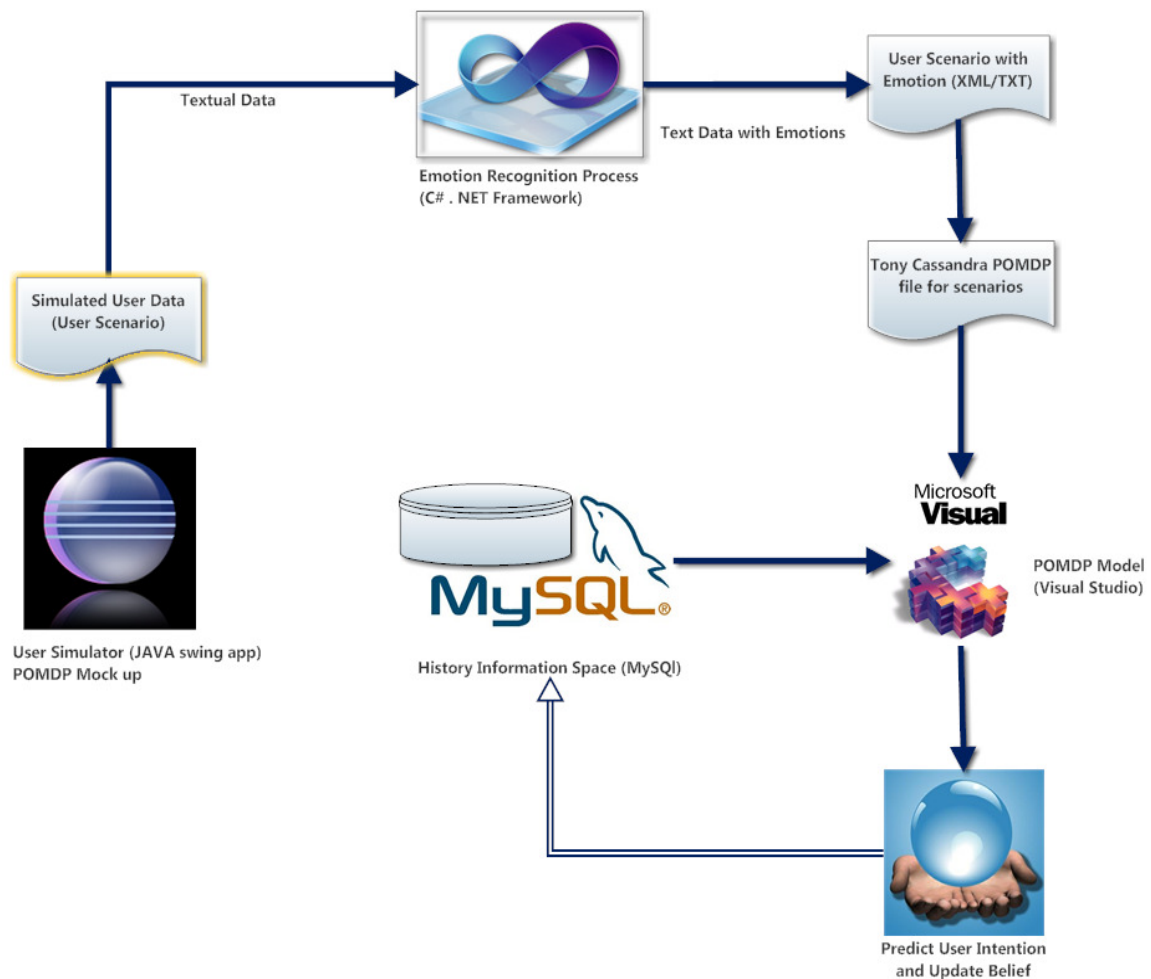
Figure 5.2.2: Overall Implementation Process of the Proposed Approach

71

5.2.1 POMDP File Specification

In the process of execution, the POMDP problem specification file is in the organization of Tony Cassandra [45] and the dialogue specification parser was developed by Bui [46] at the Human Media Interaction research group of the University of Twente is used. The POMDP's input file follows the Tony Cassandra's format [6] which can be handled by the POMDP solver. It is the formal problem specification file which encoded the domain problem under the distinct composition and semantics. Tony Cassandra POMDP specification file must have 5 important objects which specify the discount value, states, actions and observations at the beginning. Figure 5.2.1.1 shows the beginning objects definition. The order can be in any sequences and all of them must precede specifications of transition probabilities, observation probabilities and rewards.

```
discount: %f
values: [ reward, cost ]
states: [ %d, <list of states> ]
actions: [ %d, <list of actions> ]
observations: [ %d, <list of observations> ]
```

Figure 5.2.1.1: Tony Cassandra [41] File Objects

The transition possibilities can be specified in the following format:

T: <action> : <start-state> : <end-state> %f

and observation probabilities are specified in a little similar way with transition probabilities in following format:

O: <action>: <end-state> : <observation> %f

The reward model is specified in this following format:

R: <action>: <start-state> : <end-state> : <observation> %f

72

For any of the entries appeared in the above, an asterisk * for either < state >, < action >, < observation > indicates a wildcard which means this item will be expanded to all existing entities. For the simulated pizza ordering system, the POMDP specification format is designed based on the experiences and domain knowledge. Since it is an individual POMDP file we specify a unique file for each of the user goals and user actions. The system can perform 4 types of actions. The number of the dialogue states are 21 including the begin state. The discount value is 0.95 in this experiment. The POMDP solver adopted in this experiment is ZMDP [47] solver. ZMDP is a software package which implements several heuristic search algorithms for POMDPs and MDPs developed by Trey Smith at the Carnegie Mellon University. ZMDP POMDP solver can work under both Linux and Mac operating systems. To solve the POMDP problem in our experiments, heuristic search value interaction algorithm (SARSOP) [48] is used. SAROPS is a point-based approximation algorithm that maintains both upper and lower bounds on the optimal value function, allowing it to use effective heuristics for action and observation selection, and to provide the policy that it generates. The following figures shows examples for POMDP file specification for pizza ordering system.

73

```
qa-dialogue-simple - Notepad
File  Edit  Format  View  Help

# version  1.3 PIZZA ORDER STATES (8 states).


discount: 0.95
values: reward
states: pizza  type crust size  sauce toppings dipping-sauce combo-drink
actions: ask-repeat answer noanswer
observations: pizza  type crust size  sauce toppings combo-drink wings w-sauce unknown happy sad angry
start: pizza

T:ask-repeat:pizza
0.1  0.2  0.2     0.25 0.25    0 0 0
T:ask-repeat:type
0.1  0.15  0.2     0.2  0.2    0.05  0.05  0.05
T:ask-repeat:crust
0.1  0.15  0.2     0.2  0.2    0.05  0.05  0.05

T:ask-repeat:size
0.1  0.15  0.2     0.2  0.2    0.05  0.05  0.05
T:ask-repeat:sauce
0.1  0.15  0.2     0.35 0.05   0.05  0.05  0.05

T:ask-repeat:toppings
0.0  0.05  0.05    0.05 0.05   0.7  0.05  0.05
T:ask-repeat:dipping-sauce
0.0  0.15  0.15    0.0  0.0    0.5  0.1   0.1
T:ask-repeat:combo-drink
0.0  0.15  0.15    0.05 0.05   0.4  0.05  0.15

#states: pizza  type crust size  sauce toppings dipping-sauce combo-drink
T:answer:pizza
0.1  0.2  0.2     0.25 0.25    0 0 0
T:answer:type
0.1  0.15  0.2     0.2  0.2    0.05  0.05  0.05
T:answer:crust
0.1  0.15  0.2     0.2  0.2    0.05  0.05  0.05
T:answer:size
0.1  0.15  0.2     0.2  0.2    0.05  0.05  0.05
T:answer:sauce
0.1  0.15  0.2     0.2  0.2    0.05  0.05  0.05
T:answer:toppings
0.05  0.15  0.15    0.1  0.1    0.15  0.15  0.15
T:answer:dipping-sauce
0.05  0.15  0.15    0.1  0.1    0.15  0.15  0.15
T:answer:combo-drink
0.05  0.15  0.15    0.1  0.1    0.15  0.15  0.15

#states: pizza  type crust size  sauce toppings dipping-sauce combo-drink
T:noanswer:pizza
0.1  0.2  0.2     0.25 0.25    0 0 0
T:noanswer:type
0.1  0.15  0.2     0.2  0.2    0.05  0.05  0.05
T:noanswer:crust
0.1  0.15  0.2     0.2  0.2    0.05  0.05  0.05
T:noanswer:size
0.1  0.15  0.2     0.2  0.2    0.05  0.05  0.05
T:noanswer:sauce
0.1  0.15  0.2     0.2  0.2    0.05  0.05  0.05
T:noanswer:toppings
0.05  0.15  0.15    0.1  0.1    0.15  0.15  0.15
T:noanswer:dipping-sauce
0.05  0.15  0.15    0.1  0.1    0.15  0.15  0.15
T:noanswer:combo-drink
```

Figure 5.2.1.2: Tony Cassandra File Objects with 8 States

```
qa-dialogue-simple - Notepad
File  Edit  Format  View  Help
# version  1.7 PIZZA ORDER STATES (21 states).


discount: 0.95
values: reward
states: begin pizza  wings drinks p-reg p-veg w-hot w-buffalo d-coke d-pepsi p-cornmeal p-thin p-small p-medium p
actions: act-selectOnList act-ShowList act-YesNo
observations: pizza  type crust size  sauce toppings combo-drink wings w-sauce unknown happy sad angry
start: begin
#1      2       3       4       5       6       7       8       9       10      11      12      13      14      1
T:act-selectOnList:begin
0.01    0.33    0.33    0.33    0       0       0       0       0       0       0       0       0       0       0
T:act-selectOnList:pizza
0       0       0       0       0.25    0.25    0       0       0       0       0.25    0.25    0       0       0
T:act-selectOnList:wings
0       0       0       0       0       0       0.5     0.5     0       0       0       0       0       0       0
T:act-selectOnList:drinks
0       0       0       0       0       0       0       0       0.5     0.5     0       0       0       0       0
T:act-selectOnList:p-reg
0       0       0       0       0       0       0       0       0       0       0.5     0.5     0       0       0
T:act-selectOnList:p-veg
0       0       0       0       0       0       0       0       0       0       0.5     0.5     0       0       0
T:act-selectOnList:w-hot
0.33    0.33    0.01    0.33    0       0       0       0       0       0       0       0       0       0       0
T:act-selectOnList:w-buffalo
0.33    0.33    0.01    0.33    0       0       0       0       0       0       0       0       0       0       0
T:act-selectOnList:d-coke
0.5     0.2     0.2     0.1     0       0       0       0       0       0       0       0       0       0       0
T:act-selectOnList:d-pepsi
0.5     0.2     0.2     0.1     0       0       0       0       0       0       0       0       0       0       0
T:act-selectOnList:p-cornmeal
0       0       0       0       0       0       0       0       0       0       0       0       0.33    0.34    0
T:act-selectOnList:p-thin
0       0       0       0       0       0       0       0       0       0       0       0       0.33    0.34    0
T:act-selectOnList:p-small
0       0       0       0       0       0       0       0       0       0       0       0       0       0       0
T:act-selectOnList:p-medium
0       0       0       0       0       0       0       0       0       0       0       0       0       0       0
T:act-selectOnList:p-large
0       0       0       0       0       0       0       0       0       0       0       0       0       0       0
T:act-selectOnList:p-bbq
0       0       0       0       0       0       0       0       0       0       0       0       0       0       0
T:act-selectOnList:p-donair
0       0       0       0       0       0       0       0       0       0       0       0       0       0       0
T:act-selectOnList:p-tomatoe
0       0       0       0       0       0       0       0       0       0       0       0       0       0       0
T:act-selectOnList:p-chicken
0       0       0.5     0.5     0       0       0       0       0       0       0       0       0       0       0
T:act-selectOnList:p-pepperoni
0       0.5     0.5     0       0       0       0       0       0       0       0       0       0       0       0
T:act-selectOnList:p-greenpepper
0.1     0       0       0.9     0       0       0       0       0       0       0       0       0       0       0



#states: begin pizza  wings drinks p-reg p-veg w-hot w-buffalo d-coke d-pepsi p-cornmeal p-thin p-small p-medium
T:act-ShowList:begin
0       0.6     0.2     0.2     0       0       0       0       0       0       0       0       0       0       0
T:act-ShowList:pizza
0       0       0       0       0.5     0.5     0       0       0       0       0       0       0       0       0
T:act-ShowList:wings
0       0       0       0       0       0       0.5     0.5     0       0       0       0       0       0       0
T:act-ShowList:drinks
0       0       0       0       0       0       0       0       0.5     0.5     0       0       0       0       0
T:act-ShowList:p-reg
```

Figure 5.2.1.3: Tony Cassandra File Objects with 21 States

5.2.2 Generating Policy File

By receiving the POMDP specification file in Tony Cassandra's format, the ZMDP solver produces the *out.policy* file which specifies each action and state for selected POMDP file along with corresponding approximate optimal solution. In POMDP policy file, a set of lower bound values is set with an alpha vector and the corresponding actions are presented. With a current belief b, the lower bound on the expected long-term reward starting from b and that action leading to the expected lower bound can be known. In this experiment, the ZMDP solver was made to run for 17.66 minutes for the file specified and then stopped for generating the POMDP policy file.

Figure 5.2.2.1: Generating Policy from POMDPSOL Binary File

Figure 5.2.2.2: Terminating to Create the Output Policy File

The generated policy file and the original POMDP file are given as inputs to the POMDP solver and the evaluator to make multiple runs and check the number of runs it takes to print the result. As well, we can utilize them to validate the POMDP state evaluation which is shown in Figure 5.2.2.3 below.

Figure 5.2.2.3: Policy Output File

5.2.3 Test Case 1
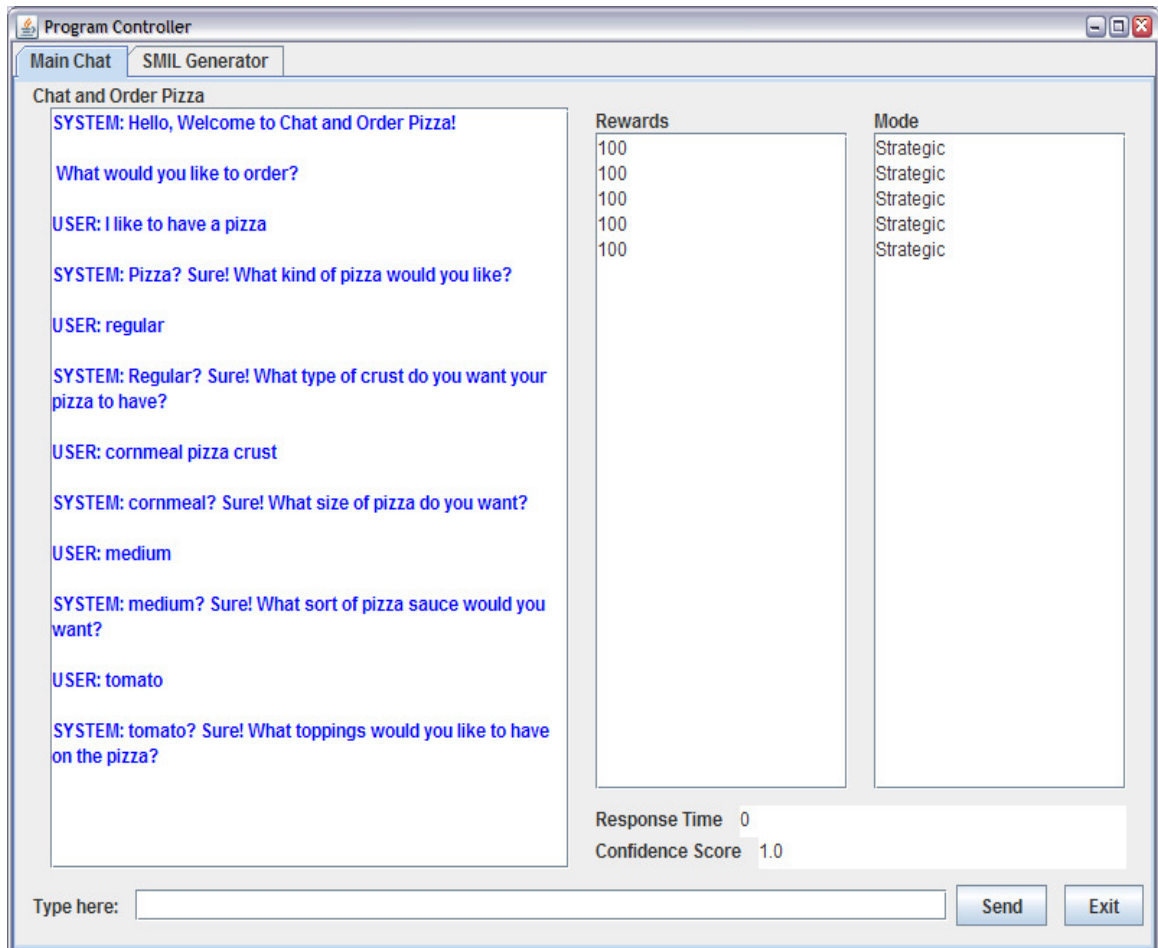
Figure 5.2.3.1: Test Case 1 in POMDP Mock up

We would set the above selected states and observations in the POMDP file and run the POMDP solver to predict the scenario with the user goal. The scenario outcome is as follows:

<Regular, medium pizza with cornmeal crust and tomato sauce>

This above situation is set as the user goal and we try to predict this using the solver and the results are as follows. The simulation only predicts when every user input is satisfactory.

Figure 5.2.3.2: Test Case 1 POMDP Simulation

Simulation	Output
Total runs	1000
Number of times Scenario reached	833
Total turns	4220
Average turns per run	4
Standard deviation:	3.882622246293481
Average reward per turn	1.7209302325581395

Table 5.2.3.3: Test Case 1 Results

5.2.4 Test Case 2
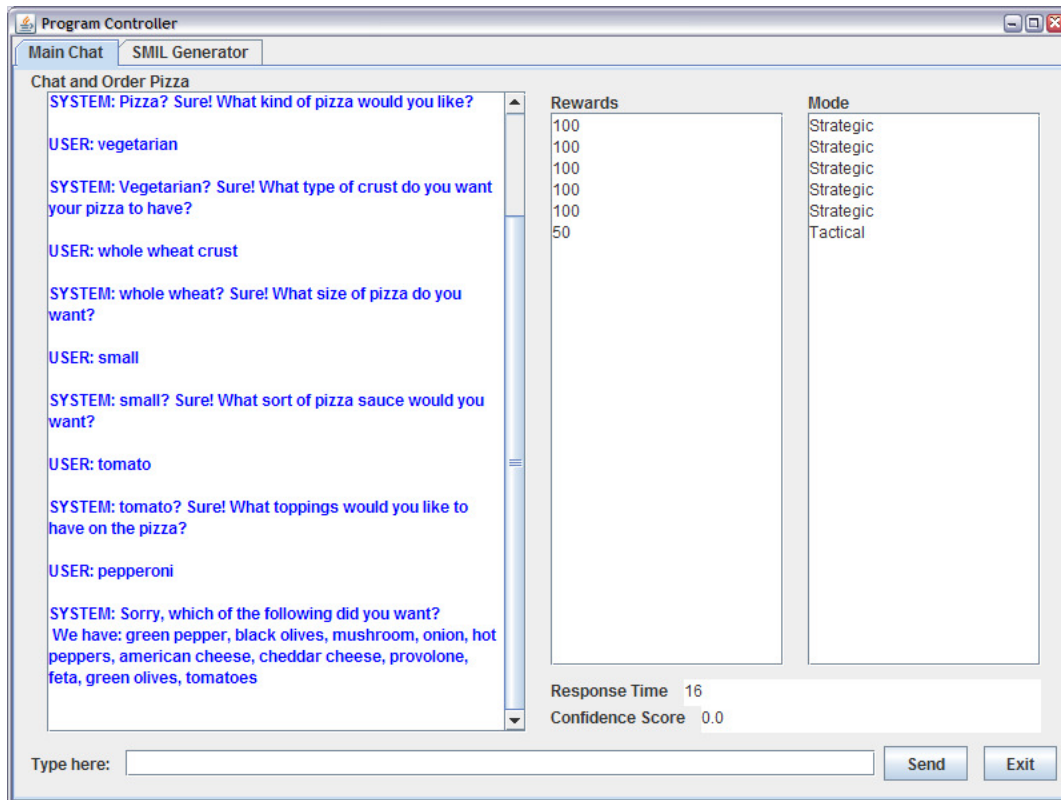
Figure 5.2.4.1: Test Case 2 in POMDP Mock up

In this case we would set the above selected states and observations in the POMDP file and run the POMDP solver to predict the scenario with the user goal. The scenario here is as follows:

<Regular, small pizza with whole wheat crust and tomato sauce and topped with pepperoni>

This above situation is set as the user goal. We try to predict this using the solver, but the system does not arrive at a solution as the simulation only predicts when every user input is appropriate. It is shown in Figure 5.2.4.2.

Figure 5.2.4.2: Test Case 2 POMDP Simulation

Since there exists a conflict in the user input, the POMDP does not solve the policy as the belief updated or the initial belief has a value to a meat toppings for a pizza whereas the state chosen earlier is 'p-veg' which is a vegetarian pizza. Hence there is only the first line written in the policy file, which gives out an error when we try to simulate.

5.2.5 Test Case 3
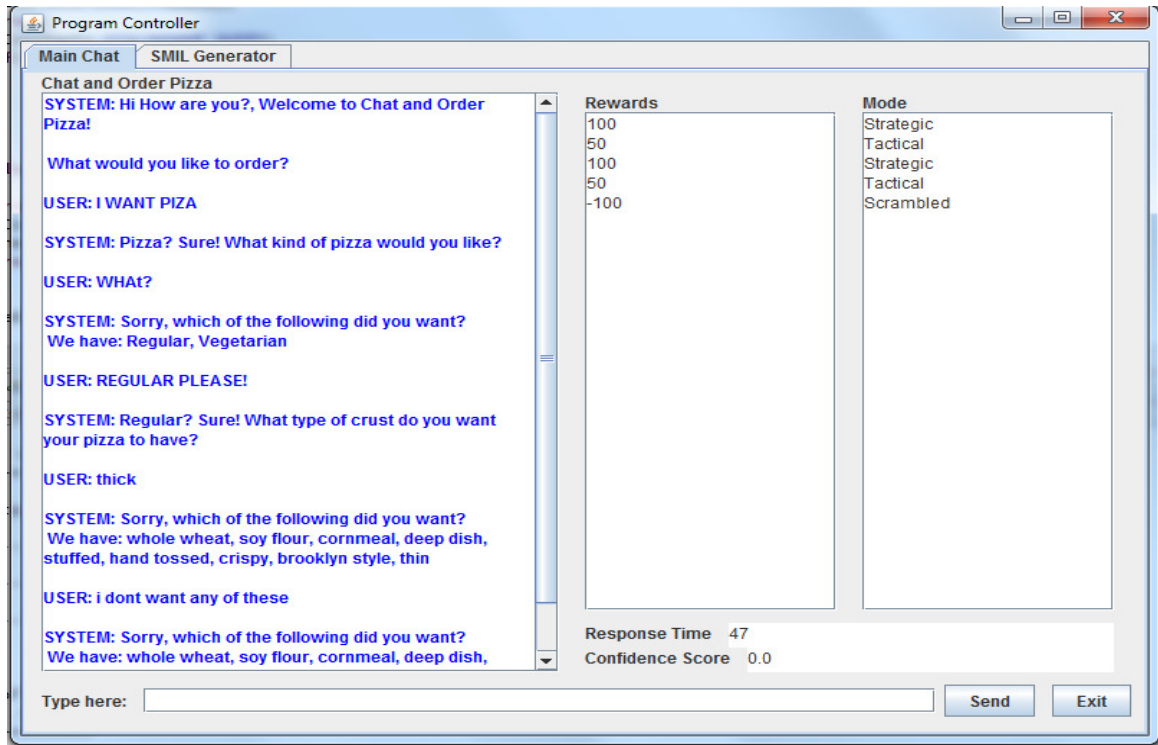
Figure 5.2.5.1: Test Case 3 in POMDP Mock up

In the above specified case, the user has become angry in emotion since he did not get a 'thick' crust as it is not there in the menu. The system will have to run through the information space to get the possible result which is the maximum number of previously returned scenario and try acting randomly to see if the user wants the same.

Simulation	Output
Total runs	10
Number of times Scenario reached	9
Total turns	2
Average turns per run	2
Standard deviation:	0.96978843211
Average reward per turn	2.6

Table 5.2.5.2: Test Case 3 Results

Figure 5.2.5.3: The 10 runs for the Output File

84

The simulated results from the mock up are as follows:

Emotion: Pleased

USER: I WANT PIZA

Rewards: 100

Confidence: 1.0

++++++++++++++++++++++++++++++

Emotion: Displeased

USER: WHAT?

Rewards: 50

Confidence: 0.0

++++++++++++++++++++++++++++++

Emotion: Pleased

USER: REGULAR PLEASE!

Rewards: 100

Confidence: 1.0

++++++++++++++++++++++++++++++

Emotion: Displeased

USER: thick

Rewards: 50

Confidence: 0.0

++++++++++++++++++++++++++++++

Emotion: Fear

USER: i dont want any of these

Rewards: -100

Confidence: 0.0

5.3 Results and Discussion

We simulated five different test cases to analyse the performance of our new approach. The above specified test cases demonstrate the efficiency of the new improved Modified POMDP in comparison to the previous work, which are shown in Table 5.3.2, where we have compared the results with the benchmarks and baseline works for 1000 runs for a total of about 233 similar scenarios. If the system achieves higher confidence scores it means that it can understand the user utterances better in a regular or noisy environment.

	Baseline 1[7] *Intention level only*	*Baseline 2[6]* *Intention level only*	*Proposed Work* *Intention + Emotion*
Average Number of Turns for scenarios	8	11	5
Average number of times scenario achieved per 1000 turns	712	745	822
Accuracy (percentage)	71	75	82
Standard Deviation	5.4	4.6	3.8

Table 5.3.1: Comparison Results

The above table infers that it outperforms the two baseline works in performance, efficiency and standard deviation. The baselines' dialogues have higher standard deviation given that the proportion of number of turns per dialogue is more disperse. The

87

dialogue gathered in the new modified approach has a smaller deviation since the successful dialogues are usually those which require the minimum number of turns to achieve the objective which is the user goal. This is also basically because of the addition of emotion values in the observation as it makes the history space more structured.

```
C:\Windows\system32\cmd.exe
878.64  3248     80059      16.9205     17.122      0.201557    45      11581
879.468 3250     80109      16.9205     17.122      0.201557    45      11588
880.259 3252     80157      16.9205     17.122      0.201557    44      11595
881.685 3254     80205      16.9205     17.122      0.201557    44      11598
882.78  3256     80255      16.9205     17.122      0.201544    45      11608
883.198 3258     80300      16.9205     17.122      0.201543    44      11610
885.047 3260     80351      16.9205     17.122      0.201537    45      11618
886.004 3262     80405      16.9205     17.122      0.201535    45      11627
886.735 3264     80453      16.9205     17.122      0.201498    45      11633
887.711 3266     80505      16.9205     17.122      0.201496    44      11642
889.738 3268     80557      16.9205     17.1219     0.201466    45      11653
890.682 3270     80605      16.9205     17.1219     0.201463    46      11661
891.352 3272     80657      16.9205     17.1219     0.201463    45      11666
892.648 3274     80701      16.9205     17.1219     0.201462    45      11668
894.075 3276     80750      16.9205     17.1206     0.200138    45      11682
895.255 3278     80800      16.9205     17.1175     0.197035    44      11693
897.036 3280     80857      16.9205     17.1175     0.197034    44      11700
898.084 3281     80900      16.9205     17.1175     0.197033    44      11711
899.06  3284     80961      16.9205     17.117      0.196483    44      11719
899.482 3285     81000      16.9205     17.117      0.196483    44      11722
901.341 3288     81061      16.9205     17.117      0.196482    44      11729
902.338 3290     81113      16.9205     17.1169     0.196452    44      11738
902.533 3292     81150      16.9205     17.1169     0.196452    44      11738
904.297 3294     81209      16.9205     17.1169     0.196452    45      11744
904.577 3296     81255      16.9205     17.1169     0.196443    45      11745
905.04  3298     81303      16.9205     17.1169     0.196441    45      11748
905.786 3300     81353      16.9205     17.1169     0.19644     45      11754
907.4   3302     81400      16.9205     17.1169     0.196439    45      11759
907.92  3304     81453      16.9205     17.1169     0.196439    45      11763
908.316 3306     81500      16.9205     17.1169     0.196439    45      11765
910.188 3308     81550      16.9205     17.1169     0.196437    45      11773
910.433 3310     81600      16.9205     17.1169     0.196437    44      11773
911.022 3312     81650      16.9205     17.1169     0.196436    44      11777
912.891 3314     81700      16.9205     17.1169     0.196436    45      11785
913.664 3316     81750      16.9205     17.1169     0.196436    45      11791
914.243 3318     81800      16.9205     17.1169     0.196436    45      11795
914.757 3320     81850      16.9205     17.1169     0.196436    45      11798
916.629 3322     81901      16.9205     17.1169     0.196436    45      11805
917.169 3324     81951      16.9205     17.1169     0.196436    45      11809
917.766 3326     82005      16.9205     17.1169     0.196436    44      11813
919.629 3328     82059      16.9205     17.1169     0.196433    43      11821
920.339 3330     82111      16.9205     17.1169     0.196433    43      11827
921.06  3332     82150      16.9205     17.1169     0.196433    43      11833
922.388 3334     82211      16.9205     17.1169     0.196433    43      11834
923.257 3336     82250      16.9205     17.1169     0.196433    43      11842
923.737 3338     82311      16.9205     17.1169     0.196433    43      11845
924.36  3339     82350      16.9205     17.1169     0.196433    42      11850
926.106 3342     82409      16.9205     17.1169     0.196433    42      11856
927.05  3344     82459      16.9205     17.1169     0.196433    41      11864
927.807 3346     82511      16.9205     17.1169     0.196432    41      11870
929.669 3348     82559      16.9205     17.1169     0.19642     42      11878
930.095 3350     82609      16.9205     17.1169     0.196419    42      11880
930.538 3352     82659      16.9205     17.1169     0.196419    42      11882
931.086 3354     82711      16.9205     17.1169     0.196419    42      11885
932.547 3356     82750      16.9205     17.1169     0.196419    42      11888
*** Received SIGINT. User pressed control-C. ***

Terminating ...

Time    |#Trial |#Backup |LBound    |UBound    |Precision  |#Alphas |#Beliefs

932.879 3357     82785      16.9205     17.1169     0.196419    42      11890
```

Figure 5.3.2: POMDP Values with Multiple Scenarios

5.3.1 Analysis of Emotion Recognition

We achieved better accuracy with the validation experiment. Classifying sentences with the emotion as one of the six primary emotions are included in Table 5.3.1.1 and compared with the two tuning conditions on the main feature sets and a baseline. This clearly reveals the accuracy of the customized decision tree algorithm with comparison to the other two baselines mentioned.

Method	Average Accuracy
Hierarchical Classification BoW+SO[20]	55.24%
All features + sequencing(same-tune-eval)[16]	69.37%
All features + sequencing(sep-tune-eval)[16]	62.94%
Customized decision tree algorithm[1]	84.36%

Table 5.3.1.1: CDT Accuracy Comparison Table [1]

The intensity evaluation used in the system works well with the generic phrases and statements and helps by being homogenous throughout the learning process of the system. However it could be modified by including a clause to evaluate more specific

89

statements that have direct forms of emotional keywords such as 'hate', 'happy' and so on.

5.4 Conclusion

This chapter examined the efficiency and effectiveness of the new proposed modified POMDP system with emotions. The emotion recognition process using Customized Decision Tree (CDT) algorithm has showed better results than some of the existing works. The qualitative analysis supports that the proposed system is reliable with more capabilities compared to some of the baselines and other works specified. The quantitative analysis shows better results which were carried by simulating different test cases. This thesis has laid the baseline for adding emotions into the POMDP based model and given a perspective of why it is important in improving the user intention discovery technique. Some of the future work and recommendations directed towards this area of human-computer interaction can be found in the next upcoming chapter.

CHAPTER VI

CONCLUSION AND FUTURE WORKS

In this thesis, the main dialogue management approaches are observed under the pizza ordering based domain agent. As well, the history information space theory is discussed and a detailed investigation of the major approaches of dialogue management methodologies with the philosophy of information space reveals reasons for their problems. With the analysis, the problem of the existing POMDP based approach is identified which we conclude by saying it is more efficient in intention discovery while giving the user emotion as the input. The Markovian model over the belief state in the dialogue management process is challenged because it loses some noteworthy information needed for decision making. Therefore, the original POMDP-based approach applied in the dialogue management cannot detect uncertainties in the belief state which are caused by the domain knowledge constraints. Based on the theory, a modified approach is proposed to enable POMDP-based dialogue management to handle uncertainties in belief state itself by giving the user emotions and also directing the history information space. Experimental results demonstrate significant improvement by the new approach towards accurate recognition of the user's intention. The advantage is more obvious when it comes with the scenario that user has lack of knowledge and provides unreasonable information to the agent. Instead, the process still tries to suggest the user with essential possible scenario. For the future work, active investigation is

under way to include the changing trend of belief state in the process of planning for the construction of a real straight, applicable, vibrant, and instructive dialogue structure. As well, another important direction is that to investigate the more practical model to solve the POMDP based approach scale up problem. When the domain is complicated, the state space of POMDP specification file can be certainly massive and the POMDP's elucidation is reckoning exorbitant. The current active researches have already put lots of efforts in this area to design more practical background and POMDP solution procedure to speed up the approximate solution finding process. We can further import the system to mobile application by applying mobile computing techniques in the system. More importantly this approach utilizes discrete probability set to provide the belief state and update it which could be transformed to more of a continuous form which is the holy grail of robot communication or multi-agent systems. Lastly, we assume that emotion handling is enough to produce user intentions but it has definitely opened up a whole set of questions such as improving the system by giving a mathematical human physiological model to the agent to produce efficient results. As well, since the POMDP approach by itself is a computationally complex method, we can try to hybridize it with another agent technique for example: BDI-POMDP approach which has a lot of potential over multi-agent gaming systems with user/agent emotions. These types of developments in the field of dialogue management will dominate the world's technology by using avatars and robots to act much more naturally in providing support to the human beings.

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VITA AUCTORIS

Sivaraman Sriram was born in 1986 in Chennai, India. He graduated from Anna University where he obtained a B.Tech in Information Technology in 2008. He is currently a candidate for the Master's degree in Computer Science at the University of Windsor and hopes to graduate in Spring 2012.