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# Exploring Un-Intentional Body Gestures for Affective System Design

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## 1. Introduction

Imagine the following situation: a student is attempting a tutorial through an intelligent tutoring system (ITS). During the learning session, he starts scratching on his head. What might be the reason for this action? Is he anxious, or having a problem with his hair?

Now imagine how effective the intelligent tutoring system (ITS) could be if it could correctly realize students' mental state and consequently adopt a suitable instructive strategy to address the situation.

Human affect-sensitive system such as envisioned here, capable of interpreting its users' affect and promising applications proposed by Picard (2000) and others (Brave & Nass, 2002) are source of inspiration for growing interest in researching affective systems. However, reliable recognition of affect needs to address uncertainty and context dependency when mapping affect from human behavioral cues. Uncertainty comes from the fact that affective interpretations vary from person to person and likewise being context dependent these interpretations vary with situation quite often. Here, we discuss our approach to address both of these issues.

As such no precise and generally agreed definition of affect or emotion exists. Recently, (Minsky, 2006) describes emotional state as not different from the process such as thinking. Human affect may consist of emotional and/or mental state of a person. Beside verbal expression there are non-verbal means of expressing affect by humans. They include visual cues that may inform about the human affective state. Gestures from face, hand and body are part of human body language (Sebe & Lew, 2003), and may communicate affect in various situations. We consider human body gestures for affect interpretation, and use them for designing affective systems.

In this chapter, we report an extension of our earlier work (Abbasi et al., 2007) that explores the presence of body gestures that we found as common among a group of students attending a class lecture. Most of these gestures involve hand movements around the face and are unintentional in nature. We map these gestures to affective states reported by students. We propose using this information for designing an intelligent tutoring system or an affective class barometer.

To address the uncertainty in subjective interpretations, we propose using a probabilistic approach. These interpretations are dependent on situational context as they occur in a

particular scenario such as in a class room situation. Preliminary analyses from our proposed model advocates suitability and applicability of our approach. At the end, we conclude with limitations and future directions for this work.

## 2. Related work

Affective computing is an emerging approach for intelligent and effective system design while vision-based human affect analysis proposes execution of this approach. Some researchers have considered extracting affect automatically from facial expressions (Pantic & Rothkrantz, 2000; Pantic et al., 2005; Tian et al., 2005) while others have analyzed hand gestures to extract affective information (Kim et al., 2006; Lee, 2006).

A recent survey by Mitra & Acharya (2007) provides current state of art in gesture recognition but this development still needs reliable means to map gestures to correct affective states that can be used for devising valuable affective systems. Although, previous works are much focused on improving detection methods, and mostly exclude contextual information, yet they do augment the overall research effort.

Earlier studies by Darwin (1872) on facial expression and those followed by Ekman & Friesen (1975, 1978) report the presence of universal emotional categories. Mehrabian (1968) reveals through his studies that 55 percent of emotional message in face-face communication results from body language. Ambady & Rosenthal (1992) suggest both facial expressions and body gestures as most significant human behavioural cues. Lately, Gunes & Piccardi (2007) show better recognition results using both modalities while augmenting their work (Gunes & Piccardi, 2006) on forming a database of both modalities.

Dadgostar et al. (2005) utilize non-verbal information to assist intelligent tutoring system. They relate gestures with students' skills. Pantic et al. (2005) and Kapoor et al. (2004) use audio-visual channels for affect recognition while Balomenos et al. (2004) consider visual channel alone with multiple modalities. They report recognition of six prototypic emotions, using facial expressions and hand gestures.

As such intended hand gestures, appearing in a human-to-human interaction are well established cues that communicate intentions or emotions while mostly these are used to convey sign language. On the other hand, un-intentional body movements which were not earlier perceived as showing affective state, seem to be providing informative clues about the mental or/and emotional state of a person in specific situational context.

A recent analysis of non-stylish body movements' by Bernhardt & Robinson (2007) shows promising results to detect implicitly present affect. They report that emotions such as happiness, sadness and anger could be inferred from motions such as knocking and walking. Similarly, Coulson (1992) and Burgoon et al. (2005), too correlate body actions to the emotions such as a shoulder shrug showing uncertainty or a contracted body showing fear.

Different to earlier approaches, we consider extracting affective information from people in a real world interaction such as a student-instructor interactive scenario, where we note down the observed gestures from the students and then obtain self-reports from these students in a post-experiment interview. These gestures involve unintentional hand movements relative to face such as a head scratch or an eye rub. Preliminary analysis of this work is reported in (Abbasi et al., 2007) while here we extend our work by proposing a method to exploit this information. We believe that subjective human studies such as this

are crucial as models are formed on the basis of these studies. They certainly raise the confidence level for interpreting *true* affective state.

## 3. Experimental description

We carried out the experiment involving four students attending a preliminary Japanese language class lecture. These students were from different cultural and educational backgrounds. One European, second an American-resident and rest were Asians while two of these sutdents were females. These students were recurited as volunteers.

Goal of the experiment was to record unitnetional movements of these students during the lecture. Students were not told about the exact nature of the experiment however, they were briefed about participating in a HCI study.



Fig. 1. Experimental set up (left), Post-Experiment interview with a student (right)

Two video sessions of about two hours were recorded for these students. Two passive cameras were used to record their activities as shown in Fig. 1 (left). During the first session, activities of two students were recorded, and in the second session, activities of the other pair of students were recorded. Once the recorded video was secured, the next phase was manual labeling of observable gestures by the experimenters (Refer Fig. 2).

The experimenters manually labeled the participants' hand gestures into discrete categories. These categories were determined through an initial preview of video recordings. Later, a post-experiment interview was conducted to determine the actual affective state, reported by the participants. We then compared the manual labels to the reported affect for analysis.
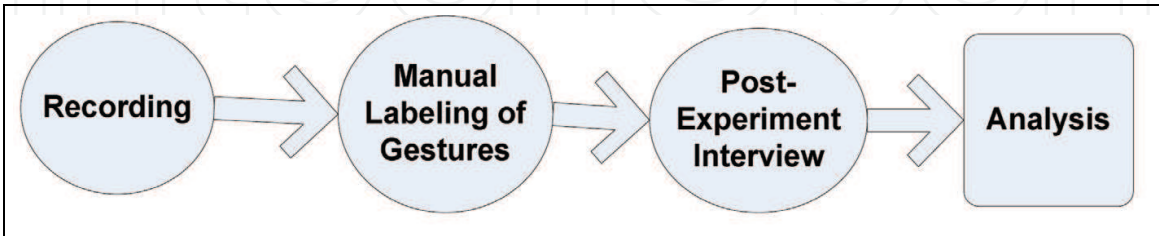


Fig. 2. Procedural steps for the Experiment

In fact, in the free format response which we retained from post-experiment interview, participants used a variety of words to describe their feelings. Therefore, we normalized them using Geneva Affect Label Code (GALC; Scherer, 2005).

Actually, GALC classifies such type of free form responses into well defined categories as it provides labels for 36 defined categories in differnt languages. Finally, we grouped participants' affective states with the corresponding images of gestures from the recorded video, some of these are shown in Fig. 3.



Fig. 3. Gestures observed during the Experiment

## 4. Data acquisition

In the data from video recordings, there were 28 gestures for student A, 37 for student B, 35 for student C and 27 for student D. Total time for each student recording was 25 minutes. Distribution of these gestures versus non-gestures for all students is shown in Fig. 4.
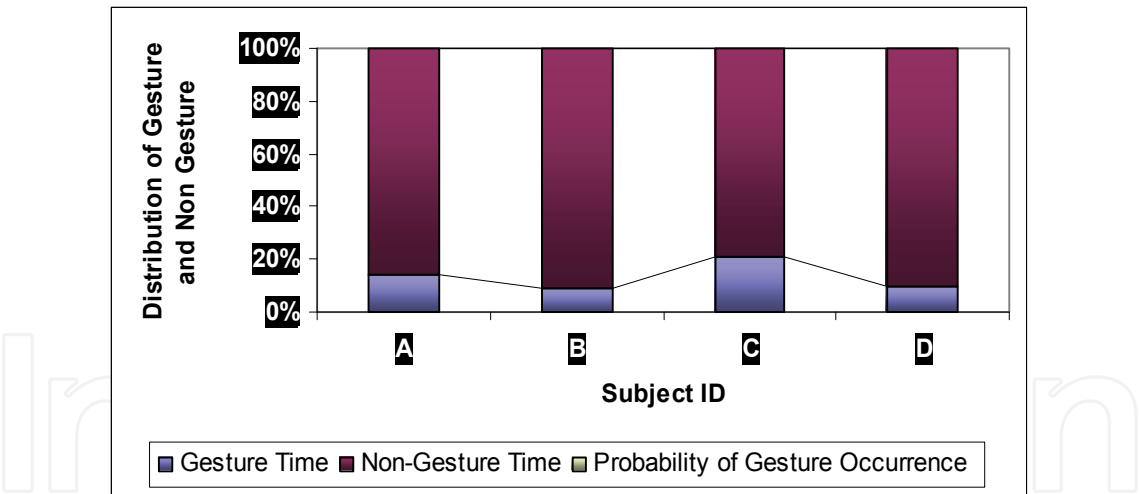


Fig. 4. Presence of gesture versus non-gestures over time for all four students

Distribution as shown in Fig. 4 refers the occurrence of gestures in a real world interaction. Average probability of occurrence of any kind of gesture calculated over all four students is 15.9 percent(with a maximum of 26.3 percent). There were about 14 gestures in all but for our analysis here; we only considered seven of these that were commonly found in the Experiment for all four students. The gestures categorized are *Head Scratch, Nose Itch, Lip Touch, Eye Rub, Chin Rest, Lip Zip and Ear Scratch.* The distribution of these gestures over all four students is shown in Fig. 5 and *Chin Rest* is the most frequent gesture among these.

From the post-experiment interview, we found that students were able to associate their gestures with some affective states. The relationship between the gestures and affective states that could be established is illustrated through Table 1.

In Table 1, the confidence level is calculated as number of times a student could correlate the gesture with the reported affective state with certainty and for remaining occasions students were reported saying *nothing* or they were not sure about the state. So, we categorized that state as having *No Emotion.* The presence of all affective states alongwith *No Emotion* state is shown in Fig. 6.
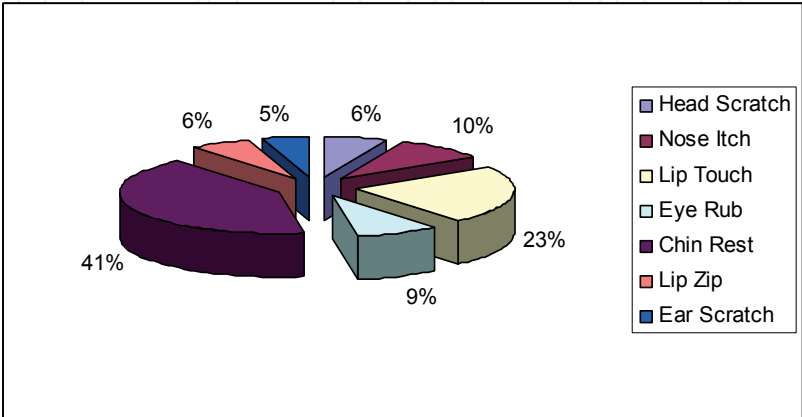


Fig. 5. Distribution of different gestures commonly found in the Experiment for all students

| Gesture | Reported Affective State | Confidence Level in Reporting |
|---|---|---|
| Head Scratch | Recalling | 100 % |
| Nose Itch | Satisified | 77.5% |
| Lip Touch | Thinking | 88.75 % |
| Eye Rub | Tired | 81 % |
| Chin Rest | Thinking | 90 % |
| Lip Zip | Bored | 100 % |
| Ear Scratch | Concentrating | 83.33% |

Table 1. Self-reported affect and co-occurring gestures with confidence level
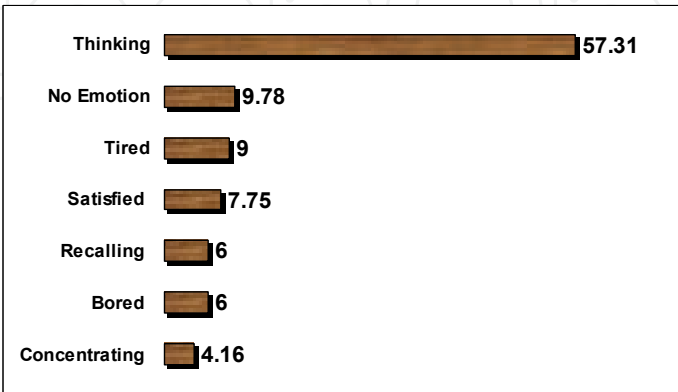


Fig. 6. Presence of affective states co-occurring with gestures, averaged over all students (in percentage of total instances)

## 5. Proposed model

From the experimental data, we formed a small domain knowledge that could be used to infer useful affective information. The novelty in our work is to propose a knowledge based affect interpretation system able to work in particular situational context, i.e. during a class lecture or student-instructor interaction. Our proposed system alongwith its component is illustrated through Fig. 7.
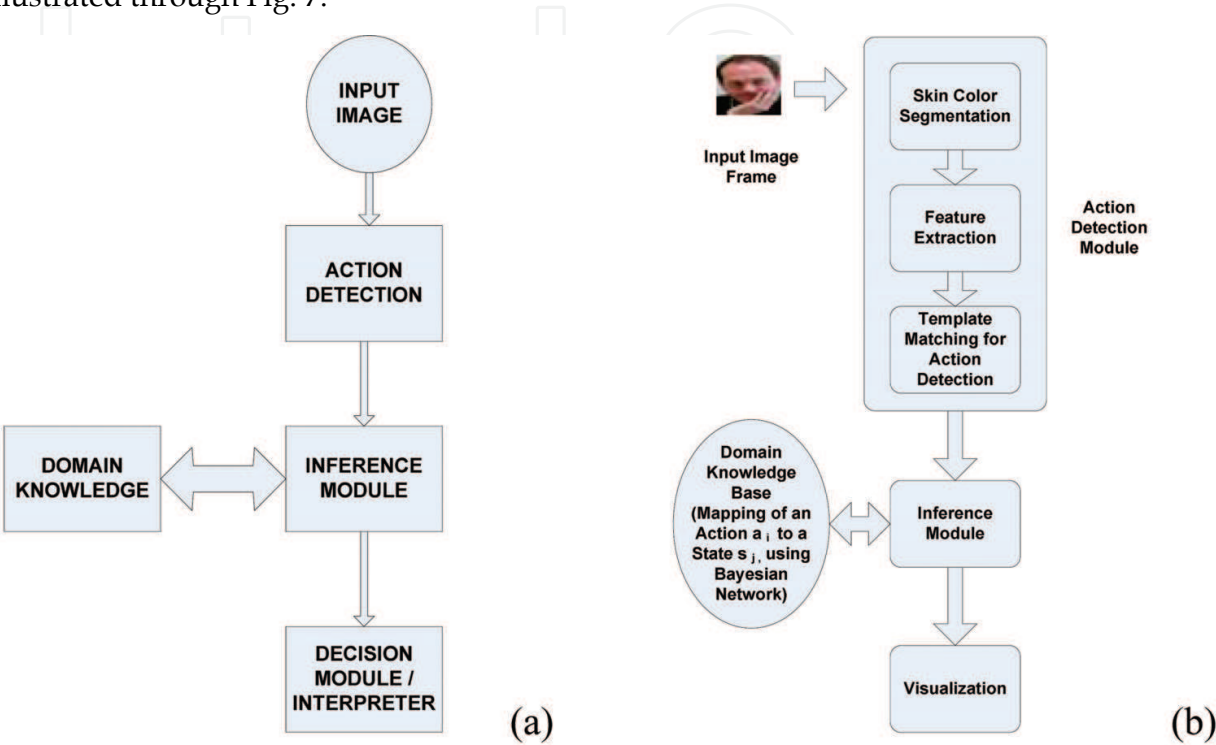


Fig. 7. (a) Conceptual model of proposed system, (b) Details of proposed system

The Action Detection module is basically the gesture detection system that may use some image processing technique to classify a particular gesture. But, for this work we consider manually labelled gestures, to provide a preliminary analysis of the proposed approach. Once a labelled gesture is given to the inference module, the next step is to infer the most probable affective state using the information from the Domain Knowledge stored in the form of prior and class conditional probabilities.

Considering the nature of data acquired from our Experiment, we use a probabilistic approach to infer useful meanings out of gesture information. In our case, number of participants and number of gestures are small. Furthermore, there is uncertainty in interpretations by the students therefore; we find probabilistic approach better than conventional statistical methods which may not be useful due of absence of complete data.

Bayesian inference uses a numerical estimate of degree of belief (prior) in a hypothesis before evidence is observed and then again computes it (posterior) after evidence is presented (Pearl, 1988). At present, Bayesian networks are widely used in artificial intelligence applications. These include medical diagnosis, image understanding, speech recognition, multi-sensor fusion and environmental modelling. Here, in our approach we use Bayesian network to model affective states as causes, and gestures as effects.

The stochastic relationship between the seven gestures and six affective states is modelled by a Bayesian network as shown in Fig. 8.
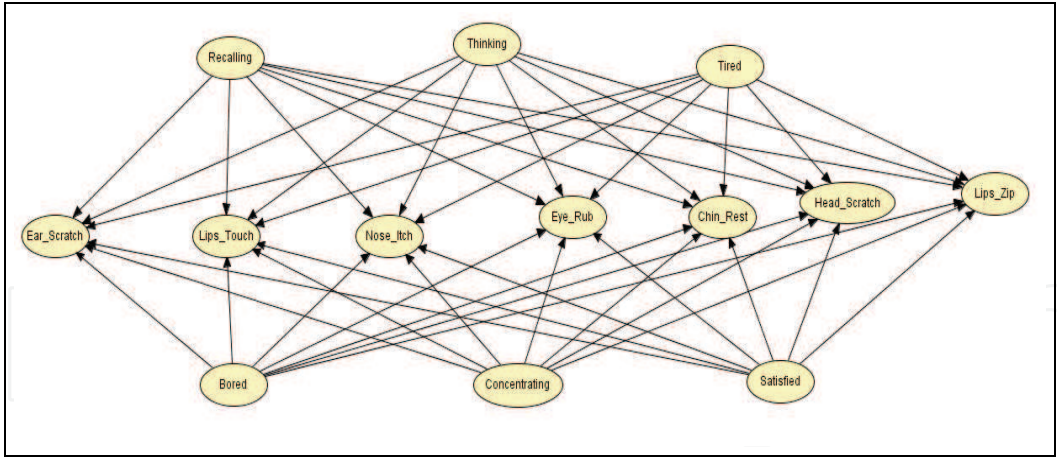
Fig. 8. Bayesian network showing cause-effect relationship of gestures and affect

## 6. Discussion on results and issues

A preliminary evaluation of the proposed Bayesian model for the four students is reported by Abbasi et al. (2008). They have reported 100 percent recognition rate over the cases where the student reported an affective state using a four fold cross validation. The classification was based on a maximum a posteriori Bayesian classifier. In contrary, recognition rate was found to be around 80 percent when they include cases where the students were uncertain.

These preliminary evaluations indicate that the proposed approach might to be suitable to model such kind of system where information involves uncertainty. However, it still needs to confirm system performance following the automation of gesture detection module. Inherently gesture detection module may involve inaccuracy that may lead to false classification of gestures thus resulting in declined model accuracy.

Furthermore, the data is secured from a limited study where the numbers of gestures is small and number of participants is few. However, these gestures are well known to occur during any interaction such as we studied but remained unnoticed as no study has found their relationship with subjects' emotional or mental state. These un-intentional clues may become part of gesture taxonomy that may be transformed to affective states as shown in Fig. 9.
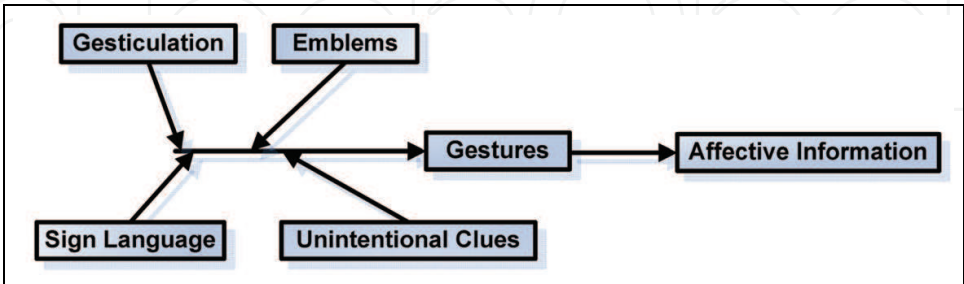


Fig. 9. Unintentional cues being part of gesture taxonomy turning to affective information

Gesticulation is referred as gestures co-occurring with speech (Kendon, 1986) which are different from autonomous gestures, conveyed independent of speech (Queck, 1994; Queck, 1995). Emblems are specific gestures used to convey an idea or concept and are more closed

to sign language. There are also other gesture types more specific to situation. An earlier work by Pavlovic et al. (1997) mention that unintentional movements of arm/hand do not convey any meaningful information, however, from our Experiment we have found that unintentional movements may be useful to predict affective states of a person in a particular situational context.

Apparently, prior to this study, we could not find any work that considers unintentional movements in context. As such human body sends message unconsciously, to signal affect or feelings but these movements cannot be identified truly without considering the context. Other unintentional movements such as folded arms, tapping forehead, crossed legs and leaning down the head could be meaningful if studied in context.

Another aspect in processing gesture information is related to the detection of a particular gesture. A recent survey by Mitra & Acharya (2007), presents the current state of art in the gesture recognition techniques however, variation in pose or style of a person or different people for the same gesture (Refer Fig. 10) is a challenging problem which needs to be resolved for a reliable gesture detection system.



Fig. 10. Few variations in the pose for the same gesture of *Chin Rest*

## 7. Conclusion & future work

Human body language has recently been explored as part of human non-verbal behavior understanding for various applications involving human-computer interaction. Body from head to toe can express itself such as an eye rub showing weariness or a chin rest showing thinking state. However, the expression and its understanding is context dependent.

We observed some unintentional movements that usually remain unnoticed while we provide meaningful correlations between these movements and probable affective state. Although, these observations are subjective but using objective measures alone to the exclusion of subjective interpretations, might be misleading to understand affective states (Boehner, 2007). Therefore, we advocate subjective analysis considering situational context to correlate actions and affect.

Natural interface between human and computers such as gaze and wink is replacing traditional keyboards and mouse clicks but at present very few systems are in commercial use. Many useful applications can benefit from studies and approach such as presented here. This includes monitoring student affective state during class lecture, web-based learning systems, automated tutoring and also drivers' or pilots' fatigue or weariness monitoring during driving or flight respectively.

In our future work, we will focus on extending scope of our analysis by gathering further data. Furthermore, we will also focus on automating gesture detection system with reasonable accuracy which is itself a challenging problem.

## 8. Acknowledgments

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**Affective Computing**

Edited by Jimmy Or

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This book provides an overview of state of the art research in Affective Computing. It presents new ideas, original results and practical experiences in this increasingly important research field. The book consists of 23 chapters categorized into four sections. Since one of the most important means of human communication is facial expression, the first section of this book (Chapters 1 to 7) presents a research on synthesis and recognition of facial expressions. Given that we not only use the face but also body movements to express ourselves, in the second section (Chapters 8 to 11) we present a research on perception and generation of emotional expressions by using full-body motions. The third section of the book (Chapters 12 to 16) presents computational models on emotion, as well as findings from neuroscience research. In the last section of the book (Chapters 17 to 22) we present applications related to affective computing.

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