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HUMAN BEHAVIORAL ANALYSIS FOR PSYCHOLOGICAL DEFECTS USING SPEECH AND LANGUAGE

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Abstract: The expression and experience of human behavior are complex and multimodal and characterized by individual and contextual heterogeneity and variability. Observational research and practice across a variety of domains from commerce to healthcare rely on speech- and language-based informatics for crucial assessment and diagnostic information and for planning and tracking response to an the opportunities as well as emerging methodologies and applications of human behavioral signal processing (BSP) technology and algorithms for quantitatively understanding and modeling typical, atypical, We highlight both the foundational speech and language processing building blocks as well as the novel processing and modeling opportunities.
and autism diagnostics to psychotherapy for addiction and marital well being, often described, human behavior in a domain-sensitive fashion.
Keywords: Affective computing; behavior; computational psychology; computational social sciences; emotions; health applications; multimodal signal processing;

I. INTRODUCTION

On the Dialog system, audio sensors can capture details of the child–clinician interaction in a consistent fashion, while analyses and modeling can quantify behavior patterns therein, including illuminating difficult to observe fine details such as dynamic variability in durations, intonation, voice quality, instances and types of nonverbal cues, etc. Critically, BSP also allows modeling interaction dynamics and its role in the diagnostic process, as well as in creating analytical capabilities for looking at fine patterning across communication modalities and over time.There is a great deal of variety in the needs and goals of **human behavioral analysis and modeling**. This, coupled with the vast heterogeneity and variability in the possible manifestations of human behavioral patterns, makes the problem of deriving universally useful and valid behavior constructs and methodologies immensely challenging.The practice in the state of the art to accomplish this has been, however, **largely manual**, relying often on trained experts.

II. RELATED WORKS:

Human behavior is complex and multifaceted. It manifests an intricate interplay among the human mind, brain, and the body. Importantly, not only does it represent the natural dynamics of an individual's internal neurological, cognitive, and physiological state, but also it reflects the influence of other agents and the environment. Behavioral expressions of an individual's actions and/or interactions hence can be widely varied depending on the Manuscript received May 28, 2012; revised August 23, 2012 and November 16, 2012; accepted December 6, 2012. Date of publication February 7, 2013; date of current version April 17, 2013. This work was supported by the National Science Foundation (NSF), the National Institutes of Health (NIH), and the U.S. Department of Defense (DoD). This paper is based on the invited lecture material presented by S. Narayanan at the International Conference on Multimedia and Expo (ICME), Barcelona, Spain, July 2011; the ACM Multimedia International Workshop on Social

Signal Processing (SSPW), Scottsdale, AZ, November–December 2011; and the Automatic Speech Recognition and Understanding Workshop (ASRU), Honolulu, HI, December 2011. The authors are with the Ming Hsieh Department of Electrical Engineering, University of Southern California, Los Angeles, CA 90089 USA (e-mail: shri@sipi.usc.edu; georgiou@sipi.usc.edu).individual’s state and the nature of the task engaged in, as well as the external influences and context. More critically, behavioral expressions are in general heterogeneous across individuals. This heterogeneity can arise from, and be attributed to, a wide range of factors ranging from age, gender, sociocultural background, to physical and mental health status and abilities, including possible differences duetoillness,disease,ordisability.Additionbilityin human behavior displays arises from the complex interplay between these and the infinite sources of variability in the cognitive demands of tasks and activities undertaken and variability in contextual factors and the environment, including the behavior of other individuals. All these factors make the understanding and automatic decoding of human behavior cues a challenging engineering problem.

2.1) Importance of Human Behavior Modeling and Prediction: Understanding, describing, and influencing human behavior is central to many domains of human endeavor. They offer a window into decoding how one is thinking and feeling. This could relate to understanding normative (‘‘typical’’) behavior patterns of an individual engaged in a task or activity. More often, it relates to detecting, analyzing, and modeling behavior deviation from what is deemed typical and in factoring out the source attributable to this variability. Consider, for example, a child engaged with a teacher in a learning activity such as reading or a problem solving exercise. In making her formative assessment, and deciding on the next course of action, the teacher may be interested in gauging not only whether the child is getting the correct answer to a question but also behavioral cues of the underlying cognitive state such as the child’s confidence or certainty [1] and socio-emotional state such as frustration, engagement, and joy in the activity [2]–[5]. Computing high level states such as uncertainty and engagement from behavioral cues can be used within a spoken dialog system such as for intelligent tutoring [6], [7]. We can draw similar examples for a variety of realms. In a customer care scenario, behavioral analysis may focus on patterns reflecting likes and dislikes of a client toward a product or service or indicators of satisfaction or lack thereof. For example, in a call center interaction, the tone of the spoken dialog can flag an irate customer, a useful element to detect for quality control [8]–[10]. Finally, no other domain exemplifies the centrality of behavioral ana- lysis and modeling more than that related to human health and well being. In particular, research and practice in psychology and psychiatry focus on diagnosing, managing, and treating atypical and distressed behavior by eliciting and/or observing behavioral cues and patterns. For exam- ple, in diagnosing whether a child has attention deficit or is on the autism spectrum, an expert often would engage the child in a series of interactive activities, targeting relevant cognitive and socio-emotional aspects, and observe the re- sulting behavior cues and codify specific patterns of inter- est (e.g., typicality of prosody, joint attention behavior)

III. PROPOSED SYSTEM

This project considers the promise, and challenges, offered by engineering techniques in facilitating human behavior analysis and modeling. Specifically, it focuses on deriving behavioral informatics from human speech and language.BSP hence considers not only just mapping the observed behavior of the target individual into categories desired by the expert, and also understanding the experts’ strategies for the elicitation of desirable patient behavior in the diagnostic interaction process.Here we use the domain of autism to illustrate some of these BSP dimensions and possibilities. Autism spectrum disorder (ASD) is a neuro_developmental disorder characterized by a triad of core deficits, including impaired social behaviors, communication, and restricted/repetitive behaviors.

Recent studies indicate that as many as 1 in 110 children are diagnosed with ASD. ASD is considered a ‘‘spectrum’’ disorder because symptom severity in each of the core domains can vary widely. Studies have shown that early diagnosis and intensive early intervention can lead to improved social and communication skills in autistic children.

IV. MODULE

4.1Feature Extraction:Automatic speech recognition (ASR) speaking styles (emotional, diffluent, and technologically unaware participants) increase acoustic variability for the Speech rate estimation: Speech rate variability carries information critical for speech understanding. When phonetic transcription is available (through manual or automatic means), speech rate is usually estimated as the number of linguistic units (phones, syllables, words, etc.) per unit time by first aligning the speech to the text (symbol) sequence, typically with an automatic speech recognizer.

4.2Emotion Recognizer:Emotional patterns at different segmental and linguistic levels (e.g., phoneme, word, part of speech) offer distinct insights into expressed emotions. For example, it was observed that emotion recognizer mean significantly differs for angry, happy, sad, and neutral speech and across different vowels. They analyzed changes in the Emotion recognizer in terms of the degree of activation in the sentences.

4.3Spoken Dialog System:On the Dialog system, audio sensors can capture details of the child–clinician interaction in a consistent fashion, while analyses and modeling can quantify behavior patterns therein, including illuminating difficult to observe fine details such as dynamic variability in durations, intonation, voice quality, instances and types of nonverbal cues, etc. Critically, BSP also allows modeling interaction dynamics and its role in the diagnostic process, as well as in creating analytical capabilities for looking at fine patterning across communication modalities and over time.

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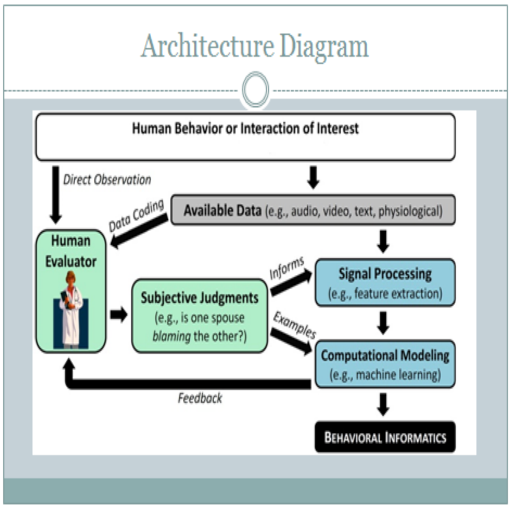
V. ARCHITECHTURE DIAGRAM



VI. CONSLUSION:

Language and Social Behavior - 54 -more speech on "feminine" topics; on what were judged to be “neutral" topics, malesinitiated more speech and talked more. The question of whether there are male-female differences language use thatare independent of the speaker's role and expertise cannot be answered from presentdata. However, it does appear that as females and males become more similar onextralinguistic dimensions, differences in the language they use become smaller.

Effects of Using GenderStereotyped Language If "women's language" is, as Lakoff claimed, a linguistic expression of women'spowerlessness in society, then its use should identify speakers as powerless regardless of their gender. There isconsiderable evidence that powerless speech results in negative evaluations of the speaker, and some indication that use of the female registeraffects the way a speaker is evaluated quite independently of his or her gender. Quinaet al. (1987 generated parallel sentences in either "masculine" or "feminine" versions and had subjects evaluate the purported male, female or sex-unidentified speaker. Authorsof the feminine versions were judged to be low on competence and high on warmth, but attributed gender did not affect speaker evaluations. Effects of stereotypicallyfeminine language on persuasive effectiveness are discussed in the section on Languageand Attitude Change above. Ng and Bradac (1993) provide a general review of power in language, as it affects communication and social influence.

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