Deception Detection by Hybrid-Pair Wireless fNIRS System

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ABSTRACT

Normal fNIRS setting up was limited by superficial physiological noises when applied into the deception detection. We designed a hybrid-pair wireless fNIRS system to improve the detection. The system takes advantages of short-pair channel to suppress the effect of physiological noises, and wireless module to improve the comfortableness of wearing it. We applied the system into a modified Guilty Knowledge Test. The experiment demonstrated that normal metrics might hint different energy consume during lying, while the regional oxygen saturation rSO2, specific in the system, is sensitive to indicate a lying.

KEYWORDS

Deception Detection, fNIRS, Hemodynamic Response, Lie Detection

INTRODUCTION

Deception detection plays a key role to judge whether a suspect is lying or identify a target from suspects in a criminal investigation (Vrij, 2000). Because exogenous signals, such as facial expression and gestures of human body could be administrated by subjects to cheat an investigation, endogenous signals, such as heart beating and breathing, had been involved to reflect subjects' psychological state (Cutrow, Parks, Lucas, & Thomas, 1972). Nevertheless, the kind of endogenous signals could also be manipulated by trained or experienced suspects (Grubin & Madsen, 2005). Feasible methods to detect lies sensitively had to be found from its definition. Social psychology defined deception as: "a communicator's deliberate attempt to foster in others a belief or understanding which the recipient considers to be untrue" (DePaulo et al., 2003). It was to say that making a lie required brain generate distinct functional activities from normal saying in order to output false contents. Hence signals originating from brain functional activity had been recorded and analyzed to detect lying (Grubin & Madsen, 2005). Electroencephalography (EEG) as an oldest electrophysiological technique had been used to detect lying. A typical study was performed by Farwell and Donchin at 1990 through event-related potential induced by Guilty Knowledge Test (Lawrence A. Farwell & Donchin, 1991). At 2012, Farwell reviewed current progress and claimed that the accuracy of detecting concealed information could reach almost 100 percent (L. A. Farwell, 2012). Though, EEG provides a way to investigate lying from scalp signals, its validity had been argued all the time (Meijer, Ben-Shakhar, Verschuere, & Donchin, 2012).

In order to recognize lying more accurately, social psychologists and neuroscientists had attempted to understand lying from different perspective. Recently, the concept of lying and progress of neuroscience had reached a new level with a brain-imaging technological advances, which is functional magnetic resonance imaging (fMRI). It relies on the theory that oxygen-level-dependent blood flow follows neuron activation in the brain (Ogawa et al., 1992). Studies employing fMRI demonstrated that the mental effort to suppress the truth and generate a false story requires greater

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neural activation in the frontal cortex than the simpler effort to recount an existing memory. As such, it suggested that a lie might be revealed from a momentary increase of blood flow or oxygen saturation in the frontal cortex region. Though fMRI worked well to indicate prefrontal cortex as region of interest during lying, it could not be applicable to scan every suspect because of the cost and limitations. Functional near infrared spectroscopy (fNIRS) reflected the same information of the brain activity as fMRI (L. Gagnon, Yucel, et al., 2012). Because of its portability and easy setting up, fNIRS was involved into the lie detection as a counterpart tool to the fMRI (Ding, Gao, Fu, & Lee, 2013; Tian, Sharma, Kozel, & Liu, 2009).

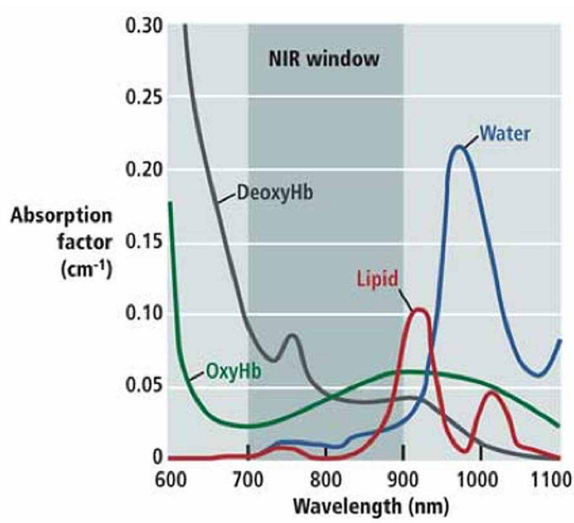
Though fNIRS could record the hemodynamic response resulting from blood flow and oxygen saturation, normal fNIRS setting up was destructed by superficial physiological signals (Takahashi et al., 2011). It consisted in the distance between a source and a detector. In a normal fNIRS system, all pairs were in the same distance, around 30 millimeters. It was unavoidable that the near infrared lights will go through the superficial tissue, such as scalp and skull. A pair of short distance was involved to suppress the superficial influence in fNIRS data (L. Gagnon, Cooper, et al., 2012; Louis Gagnon, Yücel, Boas, & Cooper, 2014). In order to utilize fNIRS to detect deception without the negative effect of superficial physiological noise, we propose to implement the detection by fNIRS with double distances of pairs. In the system, there are two kinds of pairs between a source and a detector, long (30 millimeters) and short (20 millimeters). We will compare the performance among data from a long pair, a short pair and hybrid pairs.

NEAR INFRARED SPECTROSCOPY AND SYSTEM

Near Infrared Spectroscopy

The hybrid-pair system is based on the near infrared spectroscopy. As shown in Figure 1, near infrared spectrum illustrates that there is an optical window (dark green shadow area) within the near infrared wavelengths. In the window, skin, tissue and bone are mostly transparent and light has its maximum depth of penetration in brain. Hence near infrared lights can penetrate the scalp and skull to reach the cerebral cortex. Moreover, Figure 1 presents that oxygenated hemoglobin (HbO) and deoxygenated hemoglobin (HbR) are stronger absorbers than water and lipid of near infrared lights. If a beam of

Figure 1. Absorption spectrum of oxygenated hemoglobin, deoxygenated hemoglobin, lipid and water for near infrared wavelengths



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