INFRARED IMAGING BASED ACCESS PATHWAY: A STUDY OF BASELINE CHARACTERISTICS

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INTRODUCTION

In general, the goal of access research is to identify or develop interventions that facilitate meaningful interactions between individuals with disabilities and their environment. In the recent years research and development of access technologies for individuals with profound disabilities has increased greatly. According to a recent review of access research literature, Tai et al. noted that much of the research investigates mechanical switches for those individuals possessing some retained physical movements [1]. Studies involving individuals without any retained movements, such as the locked-in population [2], are less common. For the aforementioned population, some of options that have been explored include interventions utilizing various combinations of autonomic signals [3]; mechanomyography [4]; and near infrared spectroscopy [5].

In this study we propose the use of infrared imaging as a potential physiological access pathway through measurement of thermal responses of the face. Infrared imaging is a non-contact and environment-independent way of measuring surface temperature distributions. We hypothesize that natural changes in facial temperature distribution in response to different emotional stimuli can be harnessed as a potential access pathway for individuals with severe disabilities.

The first step in developing a signal as an access pathway involves establishing an understanding of the baseline characteristics of the signal in question. This understanding is necessary to be able to detect changes from baseline, and indicates what signal analysis methods would be more appropriate in identifying those changes. The goal of this paper is to present the baseline characteristics of the mean temperature signals of specified regions of interest of the face, derived from infrared imaging. Comments about regions of interest and analysis methods that seem most promising for development of an infrared imaging based access pathway are also included [6].

SIGNAL ACQUISITION

In data acquisition sessions, infrared imaging of the face, blood volume pulse, and respiratory effort were collected from participants in a baseline state. Infrared imaging recording of facial skin temperature was achieved using a long wavelength infrared camera with an uncooled microbolometer 640 x 480 pixel array (ThermaCAM™ SC640, FLIR Systems). This infrared camera possessed a thermal sensitivity of 60 mK at 30 °C. Blood volume pulse was measured using a photoelectric pulse sensor attached to the index finger of the right hand (Model PPS, Grass Technologies). Respiratory effort was measured using a strain-gauged fabric belt secured around the chest (1370G, Grass Technologies). All signals were collected in synchrony using a LabVIEW VI. Infrared imaging recordings were obtained at 30 fps while blood volume pulse and respiratory effort signals were recorded at 60 Hz.

Infrared imaging recordings were used to generate mean temperature time series for facial regions of interest. The regions we choose to study were the forehead/supraorbital (LFH denotes the left side, RFH denotes the right side), periorbital (LPO denotes the left side, RPO denotes the right side), and nasal (NSP) regions. Figure 1 shows a single frame from an infrared recording. The boundaries of the regions of interest, as well as region labels, are indicated by the white boxes and text respectively. Mean temperature time series were obtained by calculating the mean of the temperature pixels within a region boundary for all the frames of an infrared recording.

PROTOCOL

Data was obtained from 12 asymptomatic able-bodied adults aged 24±2.9 years. Two baseline recordings were measured for each participant over one mid-morning data acquisition session. Each participant provided informed written consent in accordance to the Research Ethics Boards of Bloorview Kids Rehab and the University of Toronto.

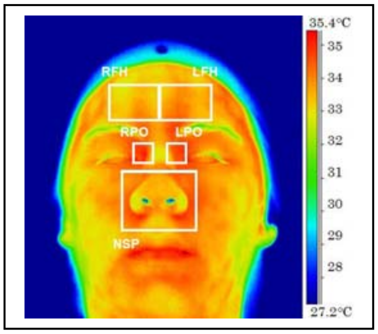

Figure 1: Example of an infrared image of the face. The white boxes indicate the regions of interest analyzed in this study. From top to bottom, the white boxes indicate the forehead, periorbital, and nasal regions respectively.

Data acquisition was performed in a temperature and humidity controlled room. Participants were asked to relax and were seated in a comfortable position approximately 1 m from the infrared camera. A schematic of the experimental setup and equipment is shown in figure 2.

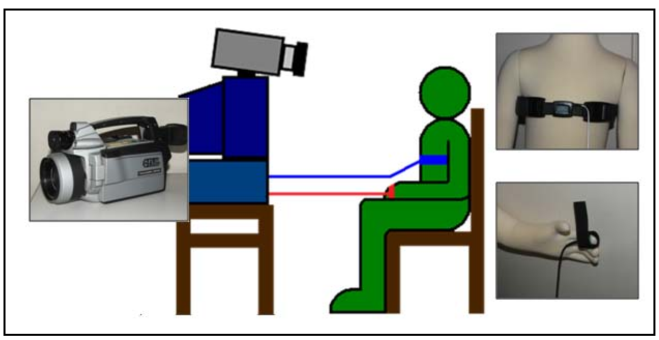

Figure 2: Experimental setup showing a schematic of participant and camera position during data acquisition. Photos show the infrared thermal camera, respiratory belt, and blood volume pulse sensor (left to right clockwise).

SIGNAL ANALYSIS

Mean temperature time series of the regions of interest (calculated as per the previous section) were analyzed in terms of stationary, frequency content and information content.

Stationarity

The reverse arrangements test was used to analyze the stationarity of the signals. This test compares the observed number of reverse arrangements with the expected number from a stationary random process. This test has been used to analyze the stationarity characteristics of other physiological signals [4, 7]. Details of this test are elucidated by Chau et al. [7].

Frequency content

The coefficients from the Short Time Fourier Transform (STFT) of the mean temperature time series were used to estimate the frequency content of the signals.

Information measures

Pearson's product moment correlation was used to analyze the correlation between the different regions of interest in baseline. The amount of information in each region was estimated using Shannon's entropy measure [8]. The amount of shared information between regions of interest was estimated using a mutual information measure [9].

RESULTS

Over 70% of the mean temperature time series, regardless of the region analyzed, were nonstationary ($p<0.05$). We also found that nearly 80% of the nonstationary signals were first-difference stationary. The frequency content analysis showed that the 90% bandwidths of the time series were below 1 Hz, with a value of approximately 0.6 Hz for all regions of interest using a STFT window size of 1024 points. The nasal and periorbital regions carried the most information at baseline based on Shannon's entropy measures. Pairwise correlation coefficients between regions were significant ($p<0.05$) and ranged from values of 0.30 (between periorbital and supraorbital regions) to 0.75 (between left and right supraorbital regions). Some degree of mutual information was shared across all regions with the greatest amount shared between the nasal and periorbital regions.

DISCUSSION

The reported results bear implications on the potential of infrared imaging of the face as an access pathway. The nonstationarity of the baseline mean temperature time series creates challenges in automatically detecting changes from baseline (i.e. elicited responses) as required in an access pathway. Because of the time-varying nature, more complex change point methods for nonstationary time series, for example Choi et al. [10], may need to be employed. However, the signals seem to be first difference stationary. Working with the first difference instead of the raw signals may be a potential means of reducing the complexity of the analyses.

The predominantly low frequency content of the time series suggests that infrared imaging would provide a modestly paced access pathway. Response times would likely be in the order of several seconds. Nasal and periorbital regions appear to be the choice access sites. At baseline the aforementioned regions seem to carry the most information content. Additionally, their high mutual information suggests capturing infrared imaging recordings from at least one of these regions may be adequate to gain information about the other.

CONCLUSION

A study of the baseline mean temperature time series of regions of the face was performed. Most of the signals were nonstationary. There are significant pairwise correlations and mutual information between regions. This study provides some insight into potential discriminatory characteristics for considering infrared imaging as an access pathway.

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REFERENCES

[1] K. Tai, S. Blain and T. Chau, “A review of emerging access technologies for individuals with severe motor impairments,” *Assistive Technology*, vol. 20, pp. 204-219, 2009.

[2] F. Plum, and J. B. Posner, *The diagnosis of stupor and coma*, 3rd Edition, Davis, Philadelphia, 1966.

[3] S. Blain, A. Mihailidis, and T. Chau, “Assessing the potential of electrodermal activity as an alternate access pathway,” *Medical Engineering Physics*, vol. 30, pp. 498-505, 2008.

[4] N. Alves and T. Chau, “Stationarity distributions of mechanomyogram signals from isometric contractions of extrinsic hand muscles during functional grasping,” *Journal of Electromyography and Kinesiology*, vol. 18, pp. 509-515, 2008.

[5] S. Luu and T. Chau, “Decoding subject preference from single-trial near-infrared spectroscopy signals,” *Journal of Neuroengineering*, vol. 6, pp. 8, 2009.

[6] B. R. Nhan and T. Chau, “Infrared thermal imaging as a physiological access pathway: a study of baseline characteristics of facial skin temperatures,” *accepted to Physiological Measurement*, 2009.

[7] T. Chau, D. Chau, M. Casas, G. Berall and D. J. Kenny, “Investigating the stationarity of paediatric aspiration signals,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 13(1), pp. 99-105, 2005.

[8] A. Porta, S. Guzzetti, N. Montano, R. F. Pagani, A. Malliani and S. Cerutti, “Entropy, entropy rate, and pattern classification as tools to typify complexity in short heart period,” *IEEE Transactions on Biomedical Engineering*, vol. 48(11), pp. 11, 2001.

[9] H. Peng, F. Long and C. Ding, “Feature selection based on mutual information: Criteria of max-dependency, max-relevance, and min-redundancy,” *IEEE Transactions on Pattern Analysis and Machine Learning*, vol. 27(8), pp. 1226-1238, 2005.

[10] H. Choi, H. Ombao and B. Ray, “Sequential change-point detection methods for nonstationary time series,” *Technometrics*, vol. 50(1), pp. 40-52, 2008.