Facial Visual Infared Stereo Vision Fusion Measurement for Internal State Estimation

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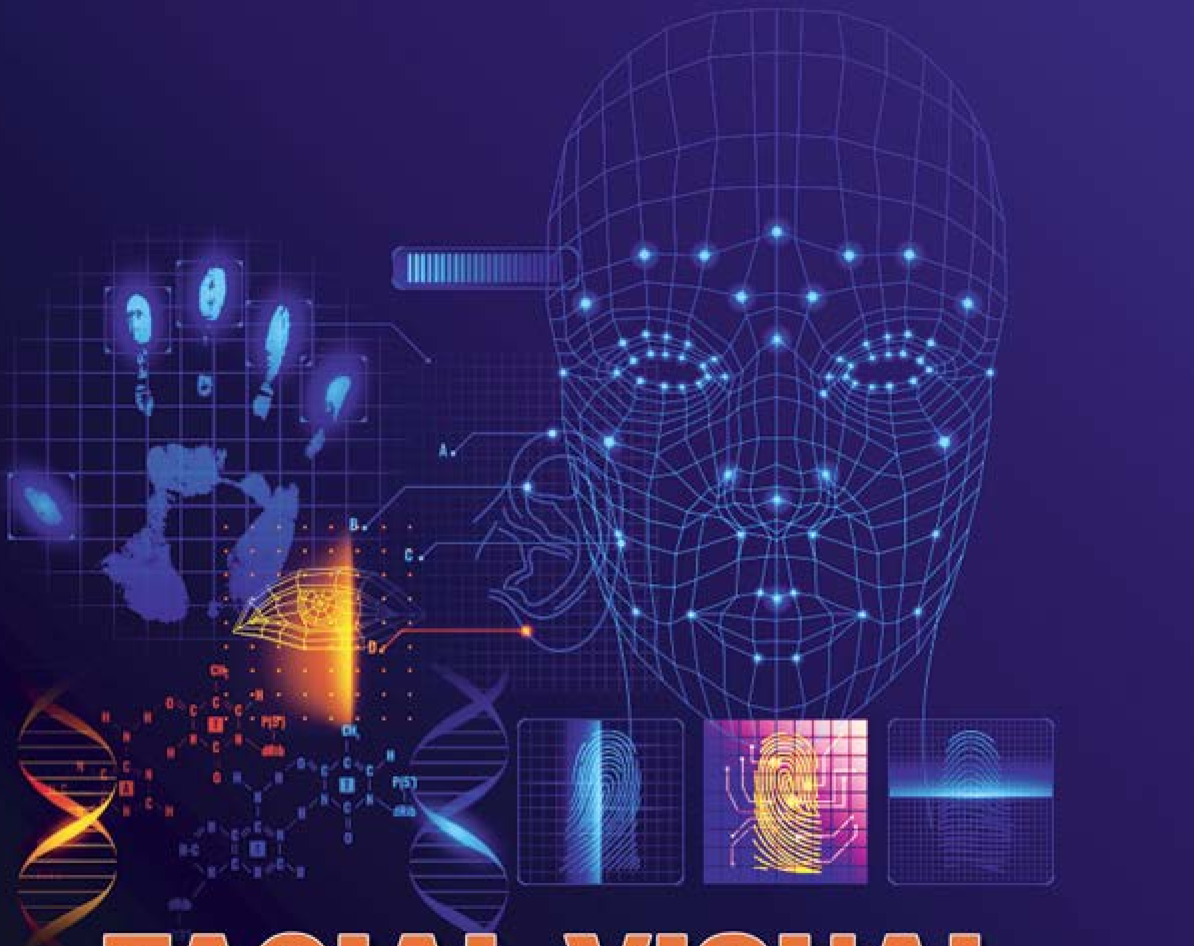
Abstract: Our main aim is to propose a vision-based measurement as an alternative to physiological measurement for recognizing mental stress. The development of this emotion recognition system involved three stages; experimental setup for vision and physiological sensing, facial feature extraction in visual-thermal domain, mental stress stimulus experiment and data analysis based on Support Vector Machine (SVM). In this thesis, 3 vision based measurement and 2 physiological measurement was implemented in the system. Vision based measurement in facial vision domain consists of 3 ROI's temperature value and blood vessel volume at supraorbital area. Two physiological measurement were done to measure the ground value which is heart rate and salivary amylase level. We also propose a new calibration chessboard attach with fever plaster to locate calibration point in stereo view. A new method of integration of two different sensors for detecting facial feature in both thermal and visual is also presented by applying nostril mask, which allows one to find facial feature namely nose area in thermal and visual domain. Extraction of thermal-visual feature images was done by using SIFT feature detector and extractor to verify the method of using nostril mask. Based on the experiment, almost 98% match was detected successfully for without glasses and 89% with glasses. Graph cut algorithm was applied to remove unwanted ROI. The recognition rate of 3 ROI's was about 90-96%. We also presented new method of automatic detection of blood vessel volume at Supraorbital monitored by LWIR camera. The recognition rate of correctly detected pixel was about 93%. An experiment to measure mental stress by using the proposed system based on SVM classification had been proposed and conducted nad showed promising results.

Keywords: Mental, physiological, stress, SVM, vision



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2022

First Published 2022

Perpustakaan Negara Malaysia Cataloguing-in-Publication Data

Mohd Norzali Hj Mohd, 1977-
FACIAL VISUAL : Infrared Stereo Vision Measurement for Internal State Estimation / MOHD NORZALI HJ MOHD
ISBN 978-967-0061-07-8
1. Stress (Psychology)--Research.
2. Emotion recognition.
3. Infrared technology.
4. Government publications--Malaysia.
I. Title.
155.9042072

Published and printed by:
Penerbit UTHM
Universiti Tun Hussein Onn Malaysia
86400 Parit Raja,
Batu Pahat, Johor
Tel: 07-453 7051 / 7454
Fax: 07-453 6145

Website: http://penerbit.uthm.edu.my
E-mail: pt@uthm.edu.my
http://e-bookstore.uthm.edu.my

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Majlis Penerbitan Ilmiah Malaysia
(MAPIM)

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ACCV 2014, LNCS, Springer-Verlag Berlin Heidelberg (2015) 73

MVA 2013, IAPR 88

International Journal of Affective Engineering (IJAE) 91

Journal of Biomedical Image Processing (JBIP) 101

International Journal of Engineering and Innovative Technology, 2013 112

VITA 121

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ACKNOWLEDGEMENTS

This research was done in the Watanabe research Laboratory, Department of Information Sciences and Biomedical Engineering, Kagoshima University , Japan.

The author would like to express his gratitude to his PhD main supervisor, Professor Dr. Watanabe Mutsumi, for he is always there to give the author advice, continuous support and guidance throughout the study. Prof. Dr. Watanabe also gives the author advices, suggestion and encouragements and arranges the opportunities to submit papers to journals and present technical papers in local and international conferences.

The author also like to thank PhD supervisors Professor Dr. Kiminori Sato and Associate Professor Dr. Satoshi Ono for the guidance, continuous advice and suggestion during defense seminar in each semester throughout the study period. Also for their effort for reviewing this book and giving their comments and suggestion.

During the research activities, another co-supervisor, Assistant Professor Dr. Kashima Masayuki has given the author helpful suggestions and assistance throughout this work, for which the author thanks greatly. The author is also very thankful to the student at the Watanabe Laboratory, Graduate School of Engineering, Kagoshima University for their cooperation in research. The author is also grateful to colleagues at Department of Computer Engineering (JEC), Faculty of Electrical and Electronic Engineering (FKEE), University of Tun Hussein Onn Malaysia (UTHM) for their advice and fruitful suggestion throughout the studies.

The author also would like to express his great appreciation to his wife Hartini Chik, children Salsabila, Syimir, Saffron, Shiraz and family members and friends for their understanding and continuous support throughout the study. This study would not be realized without their support and contributions. The author is deeply indebted to them for their sacrifices.

This study is sponsored by Ministry of Education Malaysia (MOE) and University Tun Hussein Onn Malaysia (UTHM). The author also receives partial grant aid from Ministry of Education, Culture and Sports, Science and Technology, Japan (MEXT), Japan Society for Promotion of Science (JSPS), Grants-in-Aid for Scientific Research (KAKENHI) Grant Number: 50325768 (Research and Development of the Person Internal State Automatic Recognition System Based on Integration of Pupil Blink ,Facial Temperature and Behavior Recognition, April 1, 2014 - March 31, 2017, JPY 5,000,000). The author appreciates greatly their support.

ABSTRACT

Our main aim is to propose a vision-based measurement as an alternative to physiological measurement for recognizing mental stress. The development of this emotion recognition system involved three stages: experimental setup for vision and physiological sensing, facial feature extraction in visual-thermal domain, mental stress stimulus experiment and data analysis based on Support Vector Machine (SVM). In this work, 3 vision based measurement and 2 physiological measurements was implemented in the system. Vision based measurement in facial vision domain consists of 3 Region of Interest (ROI`s) temperature value and blood vessel volume at supraorbital area. Two physiological measurements were done to measure the ground value which is heart rate and salivary amylase level. We also propose a new calibration chessboard attach with fever plaster to locate calibration point in stereo view. A new method of integration of two different sensors for detecting facial feature in both thermal and visual is also presented by applying nostril mask, which allows one to find facial feature namely nose area in thermal and visual domain. Extraction of thermal-visual feature images was done by using Scale Invariant Feature Transform (SIFT) feature detector and extractor to verify the method of using nostril mask. Based on the experiment conducted, 88.6% of correct matching was detected. In the eyes blinking experiment, almost 98% match was detected successfully for without glasses and 89% with glasses. Graph cut algorithm was applied to remove unwanted ROI. The recognition rate of 3 ROI`s was about 90-96%. We also presented new method of automatic detection of blood vessel volume at Supraorbital monitored by LWIR camera. The recognition rate of correctly detected pixel was about 93%. An experiment to measure mental stress by using the proposed system based on SVM classification had been proposed and conducted and showed promising results.

1 *Introduction*

1. THE CURRENT FOCUS OF MENTAL STRESS RESEARCH

There are escalating changes in technology and society, which bring growing demands for better techniques in dealing with wellbeing by containing everyday unavoidable life pressures and challenges. Stress is the leading threat to people because these daily demands cannot be satisfactorily handled, and is a risk to the health and social aspects of life. The term, *stress*, introduced by *Selye*, defined stress as the –specific response of the body to any demand of change. In general, stress is a complex reaction pattern that often has psychological, cognitive and behavioral components (Health Psychology - A Psychobiological Perspective, 2014). It can essentially be used to describe the wear and tear of the body experiencing changing environments, thus giving three main facets-inputs stimulus, processing and evaluation, and response (G. F. Koob, 2009).

It has been widely accepted that stress, when sufficiently powerful so that it overcomes defense mechanisms, has a range of severe impacts on immune and cardiovascular systems on individuals. As stress become chronic, it makes individuals more vulnerable to infections and incurable diseases, and slows down the body`s recovery process (S. C. Segerstrom and G. E. Miller, 2004) In addition, stress causes financial burdens on society.

Various response measures have been used to interpret stress level and fluctuations. The response measures reflect reactions of the individuals and their body to stressful situations. Some individuals may react differently to stressful events from others due to their body conditions, age, gender, experience and so on. There are computational techniques, such as artificial neural network, that can deal with these variables (M. Kumar et. al., 2007) 2. Additionally, uncertainties and complexities also exists that need to be dealt with

2 Related Works

1. INTRODUCTION

Previous studies and problems of the previous method related to vision based measurement are described in this chapter. The previous work of internal state measurement related to frequency of eye blinking in visual domain, facial skin temperature of supraorbital, periorbital and maxillary and blood vessel volume at supraorbital in thermal domain are also elaborated. Various types of past mental stress stimulus experiment, stress scale and computational techniques for modelling and classification of mental stress is also written in this chapter.

2. STEREO VIEW GEOMETRY

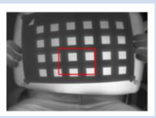
References	Collaboration Method	Method	Figure
W. Ursine et.al, "Thermal /visible autonomous stereo vision system calibration methodology for non – controlled environments", *QIRT* 2012 , ID-261, 2012.	High contrast in visible and infrared spectrum, polished copper plate coated with high emissivity paint	Using GPL openCV C++ library,	 Figure 2. Laboratory test bench
Dariusz et.al , "Calibration for 3D Reconstruction of thermal Images", *QIRT* 2008	Special Calibration Board	Using GPL openCV C++ library,	
Stephen Vidas, "A mask based approach for the geometric calibration of thermal-infrared cameras", *IEEE IAM* 6,2012.	Sized squares cut by hand or cutter and the pattern is held in front of backdrop of thermal radiances such as computer	OpenCV MSER (maximally stable external regions)	

Figure 2.1: Literature review regarding thermal-visual stereo calibration board

Figure 2.1 shows several calibration board that was proposed previously by several researchers. Researcher (N. Environments, 2012), proposed a high contrast in visible and infrared spectrum,

3 *Proposed Method*

1. INTRODUCTION

In this chapter, an integrated non-invasive measurement via imaging techniques is proposed. The main aim is to propose a vision-based measurement as an alternative to physiological measurement. The fusion of physiological vision-measurement from thermal IR and visual is shown in Figure 3.1 and 3.2. Our research consists of three vision based physiological measurements which are eye blinking from visual sensor, skin temperature of 3 ROI`s and blood vessel volume at supraorbital from thermal IR camera. The primary physical measurement in detecting mental stress is heart rate variability (N. Sharma and T. Gedeon, 2012) and salivary amylase level (M. Yamaguchi et. al., 2004) as proof by earlier researcher. The normal heart rate ranges from 60-100 bpm. In other hand, salivary amylase level (M. Yamaguchi et. al., 2004) increased significantly and is suggested as the better index of mental stress. Salivary amylase with level more than 60 *KU\L* is considered to have mental stress. Both measurement was used as a ground truth measurement in our research. The data set consisting of the proposed vision measurement is attached. In this chapter, a new calibration chessboard attaches with fever plaster to locate calibration point in stereo Visual-Thermal view is proposed. A new method of integration of two different sensors for detecting facial feature in both thermal and visual is also presented by applying nostril mask, which allows one to find facial feature namely nose area in thermal and visual domain. In this chapter also three ways to compute the relationship between visible-IR camera is explained.

4 Experimental Setup and Result

1. EXPERIMENTAL SETUP

Figure 4.1: Pulse Oximeter (SAT-2200)

Our screening environment consists of light and sound proof screening station, NEC TH7800 thermal camera (right) and USB CMOS Imaging Source DFK 22AUCO3 (left), Stimulus screening monitor, temperature and humidity sensor for monitoring screening station PICO RH-02 (Fig.4.2), Pulse Oximeter SAT-2200 (Fig.4.1) to monitor pulse rate, Nipro cocoro meter to measure salivary amylase level, responder seat and operator machine.

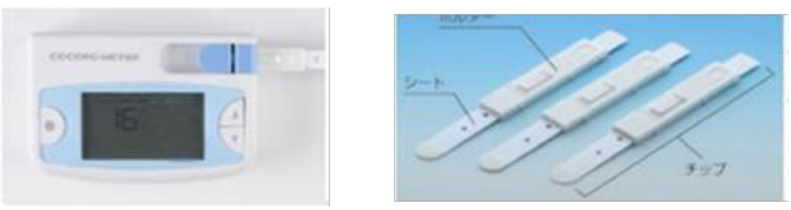


Figure 4.2: Kokorometer to measure salivary amilase level

About 20 people age from 18-30 both male and female participated in this study. The subject were asked to sit comfortably in the screening station and have him/her rest for about 5-10 minutes before and after the mental stress stimulus test. Mental Stress experiment

5 *Discussion*

1. SUMMARY BASED ON EXPERIMENTAL DATA AND RESULT

In this research, we only consider frontal face in both thermal and infrared case, as the stimulus monitor is located in front of the correspondent in our screening environment. However, facial occlusion in stereo visual-infrared is still a challenging issue. In our first experiment, the recognition rate of eyes blinking in glasses case is slightly low from without glasses because of the shadow from the light which appears on the glass surface and the frame of the glasses. However, it can be overcome by implementing proper screening environment. From this real time data, it shows that blinking frequency is highly correlated with mental stress. More experiment data should be taken in the later stage. In the second experiment, we have also found out that user stress is correlated with the increased blood flow in three facial areas of sympathetic importance which is periorbital, supraorbital and maxillary which somehow increase the temperature during stimulus. From the third and fourth experiment, we can conclude that mental stress is highly correlated with the activation of the corrugator muscle on the forehead. However, segmenting the thermal imprints of the supraorbital vessels is challenging because they are fuzzy due to thermal diffusion and exhibit significant inter-individual and intra-individual variation. On the average the diameter of the blood vessels is 10-15m, which is too small for accurate detection and 0.1◦C warmer than the adjacent skin. In the fifth experiment, the overall SVM classification accuracy is considered high 82.4563%. C.D.Katsis et. al (J. E. Kamienkowski, 2012) reported accuracy of only 79.3% using SVM classification method by features extracted from EMG, ECG, respiration and EDA bio signals. Moreover, the image processing techniques is not used by (C. D. Katsis et. al., 2008) to extract facial characteristic as the drivers need to wear a helmet. Physiological measurement of pulse rate and salivary amylase level are considered to be the most reliable measurement

6 Conclusion

1. CONCLUSION BASED ON EXPERIMENT AND RESULT

Our objective is to propose vision-based measurement as an alternative to physiological measurement. In this research three vision-based and two physiological measurements had been proposed and shows promising results. Usually in physiological measurement, combination of measures may be redundant with others and this may cause collection of unnecessarily large volumes of data and unnecessary processing time. This motivates the use of vision-based as it only requires crucial data after pattern recognition and processing of partial image. Our methodology to estimate emotional state from human subjects by extracting facial characteristic shows good performance.

2. SUMMARY AND FUTURE WORKS

Stress has been identified as a serious and growing issue adversely impacting both individuals and society, and stress recognition and classification or prediction research can lead to solve stress problem. Some benefits arising from automated stress problems. The other benefits arising from automated stress recognition and classification include improvement in education, driving and work productivity.

Stress cannot be directly measured but it can be determined by certain characteristic in primary measures. Primary measures have been considered in isolation or in some basic combination. Appropriately collected and collated physiological and physical signals can be used to measures stress, which requires consideration of aligning multi-source signals. Future work could involve investigating and modelling latencies for physiological and physical signals for fusion of primary measures for measuring stress and the use of techniques such as dynamic time warping to find an optimal alignment.

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