Modeling Stress Using Thermal Facial Patterns: A Spatio-Temporal Approach

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Modeling Stress Using Thermal Facial Patterns: A Spatio-Temporal Approach

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***Abstract*—Stress is a serious concern facing our world today, motivating the development of better objective understanding using non-intrusive means for stress recognition. The aim for the work was to use thermal imaging of facial regions to detect stress automatically. The work uses facial regions captured in videos in thermal (TS) and visible (VS) spectra and introduces our database ANU StressDB. It describes the experiment conducted for acquiring TS and VS videos of observers of stressed and not-stressed films for the ANU StressDB. Further, it presents an application of local binary patterns on three orthogonal planes (LBP-TOP) on VS and TS videos for stress recognition. It proposes a novel method to capture dynamic thermal patterns in histograms (HDTP) to utilise thermal and spatio-temporal characteristics associated in TS videos. Individual-independent support vector machine classifiers were developed for stress recognition. Results show that a fusion of facial patterns from VS and TS videos produced significantly better stress recognition rates than patterns from only VS or TS videos with p < 0.01. The best stress recognition rate was 72% and it was obtained from HDTP features fused with LBP-TOP features for TS and VS videos, respectively.**

I. Introduction

Stress is a part of everyday life and it has been widely accepted that stress, which leads to less favourable states (such as anxiety, fear or anger), is a growing concern to a person's health and well-being, social interaction and financial aspects. Stress is a natural alarm, resistance and exhaustion system [1] for the body to prepare for a fight or flight response to either defend or make the body adjust to threats and changes. Under stress, a person exerts certain emotions such as fear, anger, frustration, tension and anxiety [2]. When chronic and left untreated, stress can lead to incurable illnesses (e.g. cardiovascular diseases [3] and cancer [4]), relationship deterioration and high economic costs, especially in developed countries [5]. It is important to recognise stress early to diminish the risks. Stress research is beneficial to our society with a range of benefits, motivating interest and posing technical challenges in Computer Science. Various computational techniques have been used to objectively recognise stress using models based on techniques such as Bayesian networks [6], decision trees [7], support vector machines [8] and artificial neural networks [9]. These techniques have used a range of physiological (e.g. heart activity [10], brain activity [11], galvanic skin response [12] and skin temperature [7]) and physical (e.g. eye gaze [6], facial information [13]) measures for stress as inputs. Physiological signal acquisition requires sensors to be in contact with a person and it can be obtrusive. In addition, the physiological sensors are usually required to be placed on specific locations of the body and sensor calibration time is usually required as well, e.g. approximately five minutes are needed for the isotonic gel to settle before galvanic skin response readings can be taken satisfactorily using the BIOPAC System [14]. The trend in this area of research is leading towards obtaining symptom of stress measures through less or non-intrusive methods. This paper proposes a stress recognition method using facial imaging and does not require a body's contact with sensors like the usual physiological sensors.

A relatively new area of research is recognition of stress using facial data in thermal (TS) and visible (VS) spectra. Blood flow through superficial blood vessels, situated under the skin and above the bone and muscle layer of the human body, allow TS images to be captured. Literature has reported that stress can be successfully detected from thermal imaging [15] due to changes in skin temperature under stress. In addition, facial expressions have been analysed [16] and classified [17] using TS imaging. Commonly, VS imaging has been used for modelling affective computing problems such as depression [18], emotion [19], and pain analysis [20]. However from our understanding, the literature has not developed computational models for stress recognition using both TS and VS imaging together yet. This paper addresses this gap and presents a computational method to use information from temporal and texture characteristics of facial regions for stress recognition.

Facial expression analysis is a long researched problem. Techniques have been developed for analysing the temporal dynamics of the facial muscle movements. Vision based stress analysis can take inspiration from this vast field of facial expression analysis. Techniques have been developed for texture analysis in the temporal domain and have been successfully applied to obtain temporal information from facial data. In particular, one that has gained attention and is suitable for the work in this paper is local binary patterns on three orthogonal planes (LBP-TOP) [21]. It provides features that incorporate appearance and motion, and is robust to illumination variations and image transformations. This paper presents an application of LBP-TOP to TS and VS videos.

There are various forms of stressors, i.e. demands or stimuli that cause stress including playing video (action) games [22], solving difficult mathematical / logical problems [23] and listening to energetic music [24]. Among them are films, which are used to stimulate stress in the work presented in this paper. In this work, we define stress as defined in [3] and develop a computed stress measure [3] using facial imaging in VS and TS. Our work analyses dynamic facial expressions that are as natural as possible elicited by a typical

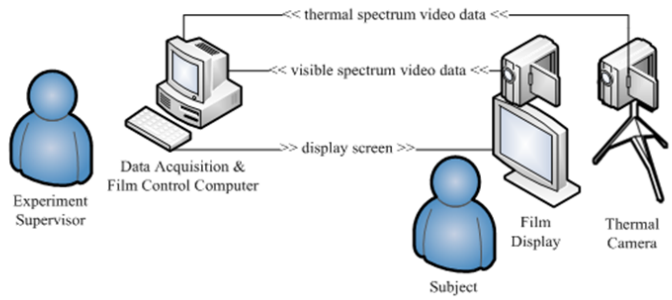


Fig. 1. *ANU StressDb recording setup:* Data capture framework visualisation.

stressful, tense or fearful environment from film clips. Unlike work generally done in the literature that uses posed facial expressions for classification [25], the work presented in this paper provides an investigation of facial expressions that are as natural as possible and elicited by a typical environment. This paper describes the method for collecting and computationally analysing data for stress recognition from TS and VS videos. An experiment was conducted to collect the data where experiment participants watched stressed and not-stressed film clips. Spatio-temporal features were extracted from the TS and VS videos and these features were provided as inputs to a support vector machine (SVM) classifier to recognise stress patterns. The paper compares the quality of the stress classifications produced from using LBP-TOP and HDTP (the proposed thermal spatio-temporal descriptor) features from TS and VS data. It concludes with a summary of the findings and suggests future work.

II. Data Collection From Film Experiment

A film experiment was conducted to collect TS and VS videos of faces of individuals while they watched films. Thirty-five graduate students consisting of 22 males and 13 females between the ages of 23 and 39 years old volunteered to be experiment participants. Each participant had to understand the experiment requirements from written experiment instructions with the guidance of an experiment instructor before they filled in the consent form. After providing consent, the participant was seated in front of an LCD display (placed between two speakers) and the TS and VS video cameras were calibrated to capture videos of frontal facial regions. The instructor started the films, which triggered a blank screen with the numbers 3, 2 and 1 transitioning in and out slowly with one before the other for 15 seconds. The reason for the countdown display and the blank screen was for participants to move away from their thoughts at the time and get ready to pay attention to the films that were about to start. This approach was similar to the experiments for similar work in [26]. Subsequent to the countdown display, a blank screen was shown for 15 seconds, which was followed by a sequence of film clips. After watching the films, the participant had to fill in a survey, which related to the films they watched and provided validation for the film stress labels. The experiment took approximately 45min for each participant.

Participants watched two types of films either labelled as stressed or not-stressed. Stressed films had stressful content (e.g. suspense with jumpy music) whereas not-stressed films created an illusion of meditative environments (e.g. swans and ducks paddling in a lake) and had content that was not stressful or at least was relatively less stressful compared with the films labelled as stressed. There were six film clips for each type of film. The survey done by experiment participants validated the film labels. The survey asked participants to rate the films they watched in terms of levels of stress portrayed by the film and the degree of tension and relaxation they felt. Participants found the films that were labelled stressed as stressful and films labelled not-stressed as not stressful with a statistical significance of $p < 0.001$ according to the Wilcoxon rank test. In addition, the participants found that they felt stressed when they watched the stressful films and not stressed when they watched not-stressful films with a statistical significance of $p < 0.01$.

While the participants watched the film clips, TS and VS videos of their faces were recorded. A schematic diagram of the experiment setup is shown in Figure 1. TS videos were captured using a FLIR infrared camera and VS videos were recorded using a Microsoft Webcam. The videos were recorded with a sampling rate of 30Hz and the frame width and height were 640 and 480 pixels, respectively. Each participant had a TS and VS video for each film they watched. As a consequence, a participant had 12 video clips made up of six stressed videos and six not-stressed videos. We name the database that has the collected labelled video data and its protocols the ANU Stress database (ANU StressDB).

Note the usage of the terms film and video in this paper. We use the term, film, to refer to a film that a participant watched during the experiment and we use the term, video, to refer to a video of a participant's face and its movement during the time period while they watched a film.

III. Faces in Thermal and Visible Spectra

Facial regions in VS videos were extracted using the Viola-Jones face detector [27]. Due to the different nature of TS videos from VS videos, the Viola-Jones algorithm was not appropriate for extracting facial regions, so a face detection method based on eye coordinates [28], [29] and a template matching algorithm was used. A template of a facial region was developed from the first frame of a TS video. The facial region was extracted using the *Pretty Helpful Development Functions toolbox for Face Recognition* [28], [29]. This facial region formed a template for facial regions in each video frame of the TS videos, which were extracted using MATLABs Template Matcher system[1]. The Template Matcher was set to search the minimum difference pixel-by-pixel to find the area of the frame that best matched the template. Examples of facial regions that were detected in the VS and TS videos are presented in Figure 2.

IV. Spatio-Temporal Features in Thermal and Visible Spectra

The literature claims that features from segmented image divisions of a facial image region provide more information than features directly extracted from an image of a full facial region [21] in VS. Examples of full facial regions are shown in Figure 2 and divisions of a full facial region are

[1] http://www.mathworks.com.au/help/vision/ref/vision.templatematcherclass.html

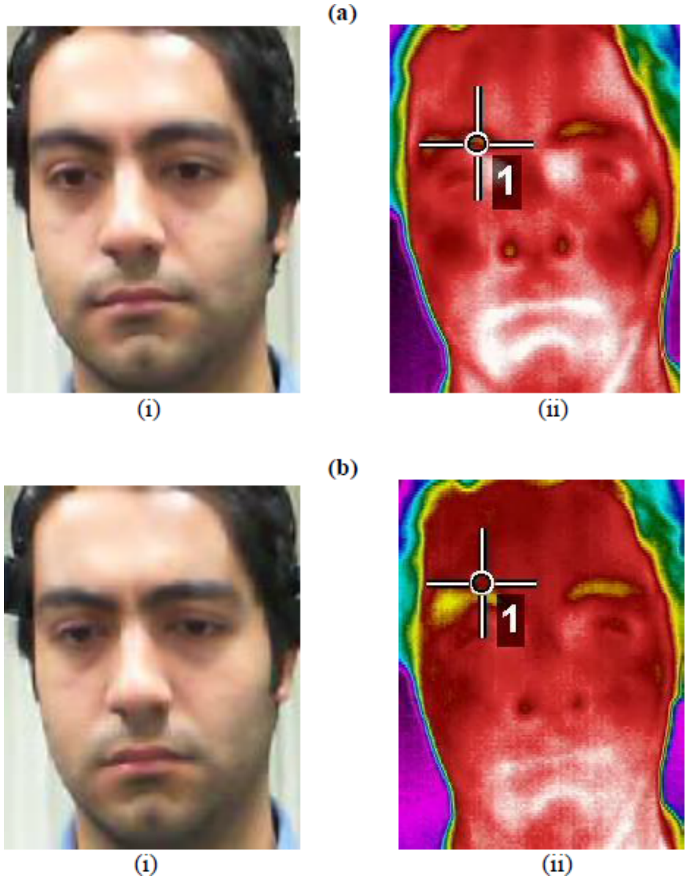


Fig. 2. *Examples of facial regions extracted from the ANU StressDB database:* (a) The subject was watching a not-stressed film clip. (b) The subject was watching a stressed film clip. (i) A frame in the visual spectrum. (ii) The corresponding frame in the thermal spectrum.

presented in Figure 3. To illustrate the claim, features from each of the divisions used in conjunction with features from the other divisions in Figure 3(i) can offer more information than features obtained from Figure 2(a)(i). The claim aligns with the results from[Text Box] classifying stress based on facial thermal characteristics [15]. As a consequence, the facial regions in this work were segmented into 3×3 divisions for each video segment forming 3×3 blocks. A block has X, Y and T components where X, Y and T represent the width, height and time components of an image sequence. Each block represented a division of a facial region spanning the number of frames of the corresponding video. LBP-TOP features were calculated for each block.

LBP-TOP is the temporal variant of local binary patterns (LBP). In LBP-TOP, LBP is applied to three planes, the XY, XT and YT planes, to describe the appearance of an image, the horizontal motion and the vertical motion, respectively. For a centre pixel O_p of an orthogonal plane O and its neighbouring pixels N_i, a decimal value is assigned to it:

$$d = \sum_{\mathcal{O}}^{XY,XT,YT} \sum_{p} \sum_{i=1}^{k} 2^{i-1} I(\mathcal{O}_p, N_i) \tag{1}$$

According to a study that investigated facial expression recognition using LBP-TOP features, VS and near-infrared images produced similar facial expression recognition rates provided that VS images had strong illumination [30]. Further, LBP-TOP features may not be able to fully exploit thermal information provided in TS videos because it is different in nature, i.e. a visualisation of temperatures, to VS videos and, thus, may not be able to capture thermal patterns for stress effectively. This motivates the development of a new set of features that exploits thermal patterns in TS videos for stress recognition. We propose a new type of feature for TS videos that captures dynamic thermal patterns in histograms (HDTP). It makes use of thermal data in each frame of a TS video of a face over the course of the video.

HDTP captures normalised dynamic thermal patterns, which enables individual-independent stress analysis. Some people may be more tolerant to some stressors than others [31], [32]. This could mean that some people may show higher degree responses to stress than others. Additionally, in general, the baseline for a human response can vary from person to person. To consider these characteristics in features used for individual-independent stress analysis, the literature has developed ways to normalise data for each participant for their type of data [33]. HDTP is defined in terms of a participant's overall thermal state to minimise individual bias in stress analysis.

A HDTP feature is calculated for each facial block region. Firstly, a statistic (consider the standard deviation) is calculated for each facial region frame for a participant for a particular block (e.g. the facial block region situated at the top right corner of the facial region in the XY plane) for all their videos for individual-independent classification systems. The statistic values from all these frames are partitioned to define empty bins. A bin has a continuous value range with a location defined from the statistic values. The bins are used to partition statistic values for each facial block region where the value for each bin is the frequency of statistic values in the block that falls within the bounds of the bin range. Consequently, a histogram for each block can be formed from the frequencies. An algorithm presenting the approach for developing histograms of dynamic thermal patterns in thermal videos is provided in Algorithm 1.

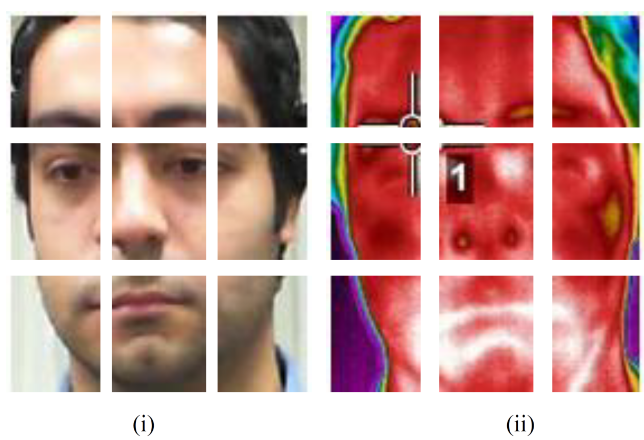


Fig. 3. *Block visualisation*: The facial region in Figure 2(a) segmented into 3×3 divisions. (i) Divisions of the frame in the visual spectrum. (ii) Divisions of the corresponding frame in the thermal spectrum.

Algorithm 1: Compute HDTP

Require: p, a participant video data set that represents a set of all videos watched by the participant. F, a function that calculates a statistic for a two-dimensional matrix.

```
for each video v(p) do
  for each facial block b(v, loc) do
    for each frame f(b) do
      s_vbf ← f(b)
    end for
  end for
end for
for each block loc(p) do
  for each facial block b(loc) do
    bin_width(b) ← calculate_bin_width(b)
    bin_locs(b) ←
    calculate_bin_locations(bin_width(b))
  end for
end for
for each video v(p) do
  for each block location loc(p) do
    for each block location loc(p) do
      h ← partition_data(b, bin_locs(b))
    end for
  end for
end for
```

As an illustration, consider that the statistic used is the standard deviation and the facial block region, for which we want to develop a histogram for, is situated at the top right corner of the facial region in the XY plane (FBR_1) for video V_1 when a participant P_i was watching film F_1. In order to create a histogram, the bin locations and sizes need to be calculated. To do this, the standard deviation needs to be calculated for all frames in FBR_1 in all videos (V_{1-12}) for P_i. This will give standard deviation values, from which the global minimum and maximum can be obtained and used to calculate the bin location and sizes. Then, the histogram for FBR_1, V_1 and P_i is calculated by filling the bins in with the standard deviation values for each frame in FBR_1. This method then provides normalised features that also takes into account the image and motion, and can be used as input to a classifier.

SVMs have been widely used in the literature to model classification problems including facial expression recognition [30], [34], [19]. Provided a set of training samples, an SVM transforms the data samples using a non-linear mapping to a higher dimension with the aim to determine a hyperplane that partitions the data by class or labels. A hyperplane is chosen based on support vectors, which are training data samples that define maximum margins from the support vectors to the hyperplane to form the best decision boundary.

Various stress classification systems using an SVM were developed, which differed in terms of the following types of input:

- $VS_{LBP-TOP}$: LBP-TOP features for VS videos
- $TS_{LBP-TOP}$: LBP-TOP features for TS videos
- TS_{HDTP}: Dynamic thermal patterns captured in histograms
- $VS_{LBP-TOP}$ + $TS_{LBP-TOP}$: $VS_{LBP-TOP}$ and $TS_{LBP-TOP}$
- $VS_{LBP-TOP}$ + TS_{HDTP}: $VS_{LBP-TOP}$ and TS_{HDTP}
- $TS_{LBP-TOP}$ + TS_{HDTP}: $TS_{LBP-TOP}$ and TS_{HDTP}
- $VS_{LBP-TOP}$ + $TS_{LBP-TOP}$ + TS_{HDTP}

V. Results and Discussion

Each of the different features derived from VS and TS facial videos using LBP-TOP and HDTP facial descriptors was provided as input to an SVM for stress classification. Facial videos of participants watching stressed films were assigned to the stressed class and videos associated with not-stressed films were assigned to the not-stressed class. Furthermore, their corresponding features were assigned to corresponding classes. Recognition rates and F-scores for the classifications were obtained using 10-fold cross-validation across participants for each type of input. The classification results from features extracted from VS and TS videos are shown in Figure 4.

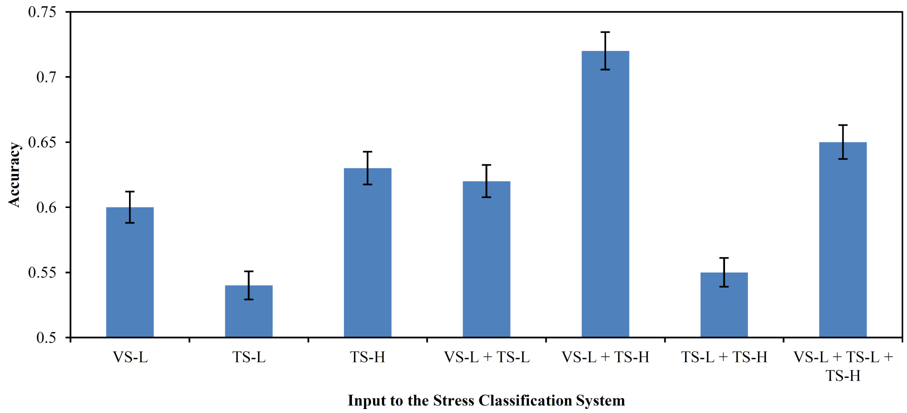
Results in Figure 4 show that when TS_{HDTP} was provided as input to the SVM classifier, there were improvements in the stress recognition measures. The best recognition measures for the SVM were obtained when $VS_{LBP-TOP}$ + TS_{HDTP} was provided as input. It produced a recognition rate that was at least 0.10 greater than the recognition rate for inputs without TS_{HDTP} where the range for recognition rates was 0.13. This provides evidence that TS_{HDTP} had a significant contribution towards the better classification performance and suggests that TS_{HDTP} captured more patterns associated with stress than $VS_{LBP-TOP}$ and $TS_{LBP-TOP}$. The performance for the classification was the lowest when $TS_{LBP-TOP}$ was provided as input.

Further, stress recognition systems provided with TS_{HDTP} as input produced significantly better stress recognition measures than inputs with TS_{HDTP} replaced by $TS_{LBP-TOP}$ ($p < 0.01$). This suggests that stress patterns were better captured by TS_{HDTP} features than $TS_{LBP-TOP}$ features.

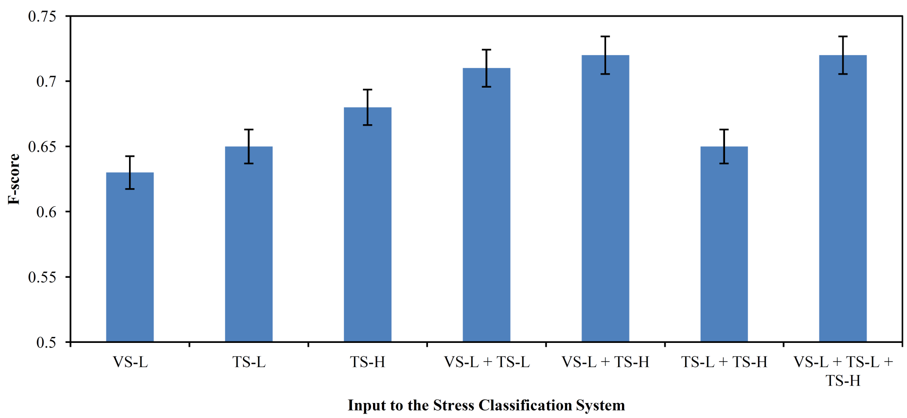
Future work could also investigate salient block selection methods to determine which blocks provide necessary stress data and improve stress recognition. Not using the irrelevant facial block regions could enable more general stress patterns to be captured and improve stress recognition. The block selection methods that could be used could be based on a genetic algorithm or correlation analysis based techniques.

VI. Conclusion

A computational classification model of stress using spatial and temporal characteristics of facial regions in videos in thermal and visual spectra was successfully developed. In the process, a TS and VS sensor based stress database was also developed. A new method for capturing patterns in thermal videos was defined – HDTP. The approach was defined so that it reduced individual bias in the computational models and enhanced participant-independent recognition of symptoms for stress. For computing the baseline for stress classification, an



(a)



(b)

Fig. 4. *Experiment Results:* Performances for SVM stress classification systems based on 10-fold cross-validation across participant data. The labels on the horizontal axis are shortened to improve readability: L and H stand for LBP-TOP and HDTP, respectively. (a) Accuracy measures for stress classification (b) F-score measures for stress classification.

SVM was used. Stress recognition rates were significantly better for classifiers provided with HDTP features instead of LBP-TOP features for TS. Future work could investigate developing more complex forms of features to capture more information for the facial block regions and examining different forms of facial block regions for stress recognition.

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