A Novel Infrared Camera-based Sedentary Time Monitoring Method

Kamrul H. Foysal and Jo Woon Chong*

Department of Electrical and Computer Engineering, Texas Tech University, Lubbock, Texas -79409, USA

Abstract

Prolonged sedentary condition has been proven to have negative impact on health [1]. In this paper, we propose an infrared (IR) camera-based sedentary time monitoring method which first classifies 1) sit-up, 2) sit lean-forward, 3) sit lean-backward, 4) lean-left, 5) lean-right, 6) standing, and 7) leaving the workspace, and measures a subject's total sedentary time as well as his/her patterns of sitting postures. Infrared camera is promising since it works even at dark environment and can protect subject's privacy due to its de-identifiable characteristics. Experimental results show that our proposed method classify 7 postures with 90% classification accuracy.

Introduction

Prolonged sedentary behavior has been identified as a potential cause of adverse health outcome (i.e. obesity, back pain, diabetes) [1]. Specifically, office workers usually have sedentary posture for several hours when they work [2]. However, limited research has been performed on alarming their sedentary time to stimulate them to exercise. To promote a healthy work environment, prolonged sedentary posture detection/alarm methods are highly demanded. There have been several approach of detecting/alarming prolonged sedentary posture using wrist watch or accelerometer [3].

In this paper, we propose an infra-red camera-based sedentary posture detection method which detects human sedentary posture time and alarms if sedentary time is longer than pre-determined threshold (more than the time suggested by the Pomodoro technique [4]). This approach adopts SURF feature detection from thermal images and classifies postures with a Support Vector Machine (SVM) classifier.

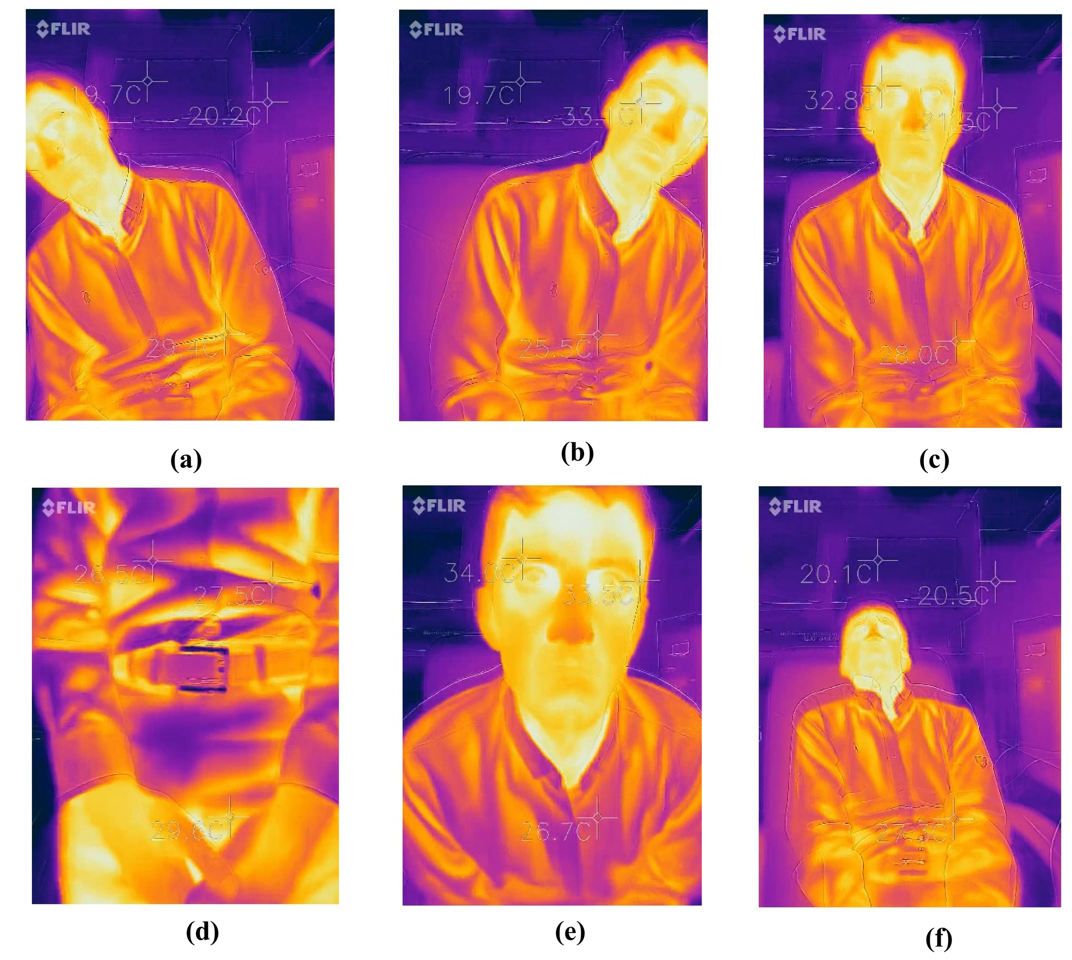

Figure 1. Representative infra-red camera images of a subject in office environment. (a) Lean Left, (b) Lean Right, (c) Sitting, (d) Standing, (e) Lean Forward and (f) Lean Backward postures.

Data Acquisition

We recruit the subjects for our experiment following the IRB2019-150. Recruited subjects are asked to sit on a chair located in front of a desk where a computer screen is placed. Here, the IR camera is installed on a desk facing a subject. A subject is asked to change their postures as follows: 1) Upright Sitting, 2) Lean Forward, 3) Lean Backward, 4) Lean Left, 5) Lean Right, 6) Stand up from the chair and 7) Leave the desk. Thermal image is collected from video recording of an infrared camera for 3 minutes and 30 seconds as shown in Figure 1. Each posture is maintained for 30 seconds. The frame rate of the video is 8 frames per second (fps).

Infrared camera is used because of its de-identifiable characteristics and capability to work in the dark. Figure 2 shows a *FLIR* Infrared camera that has been used which ranges up to 400°C, with a temperature sensitivity of 70 mK and wavelengths of 3µm–14µm.

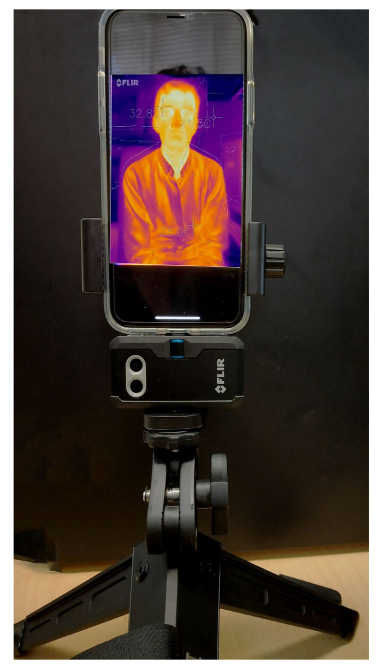

Figure 2. A smartphone application and with its setup on a desk for acquiring infrared camera images of a subject working in office environment.

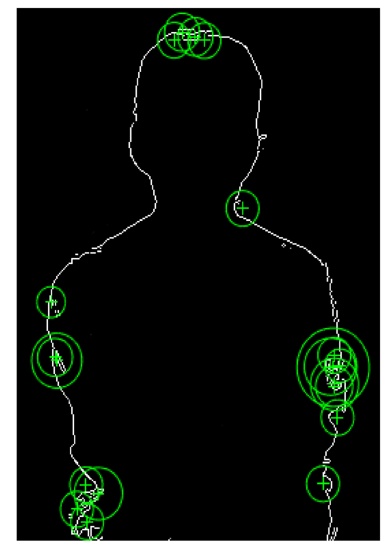

Figure 3. SURF feature points detected on an edge detected image representing sitting condition

Methods

Thermal images are collected from video recording of an infrared camera. The video recording acquired through a *FLIR* infrared camera is preprocessed. Images are extracted from the video file. The images are then resized, greyscaled and edge detected using *Sobel* edge detection method.

SURF has been used to detect the distinct features of the thermal images of different posture condition. SURF is a fast and robust local interest points detector/descriptor of images [5]. SURF uses Laplacian of Gaussian with Difference of Gaussian for finding scale-invariant characteristic points. SURF detector uses blob detection based on determinant of Hessian Matrix (from Eq. (1)) and it exploits integral images to improve feature-detection speed. SURF uses the sum of the Haar wavelet responses to describe the feature around the point of interest. SURF features are invariant to rotation, scale and partially invariant to illumination and affine transformation.

$$H(x,\sigma) = \begin{bmatrix} L_{xx}(X,\sigma) & L_{xy}(X,\sigma) \\ L_{xy}(X,\sigma) & L_{yy}(X,\sigma) \end{bmatrix} \tag{1}$$

Where $L_{xx}(X,\sigma)$ is the convolution of the Gaussian second order derivative $\frac{\partial^2}{\partial x^2} g(\sigma)$ with the image *I* in point *x*, and similarly for $L_{xy}(X,\sigma)$ and $L_{yy}(X,\sigma)$. Using SURF, the distinct feature points are extracted as a feature map from the preprocessed thermal images of each posture.

The extracted SURF descriptors are categorized from the images of each category, implementing a - means clustering method. The algorithm iteratively groups the descriptors into k mutually exclusive clusters. The resulting clusters are compact and separated by similar characteristics. Each cluster center represents a feature, or visual word.

A multiclass image category classifier is then trained with the extracted bag of features [6] using the binary Support Vector Machine (SVM). The binary SVM classifier finds a hyperplane which separates two-class data with maximal margin. The margin is defined as the distance of the closest training point to the separating hyperplane. In order to apply the SVM to multi-class problems, the one-against-all approach is taken. Given an *m*-class problem, *m* number of SVM are trained, each distinguishes images from some category *i* from images from all the other *(m-1)* categories. Given a test image, we assign it to the class with the largest SVM output.

Result

We trained the SVM with 1,033 training data images which consists of 328 sitting, 86 standing, 64 lean forward, 144 lean backward, 137 lean left, 149 lean right, 121 leaving work space images. 20 test cases were considered where the standing, lean backward, lean left, lean right, subject leaving area are always classified correctly. The other two categories, sitting and lean forward are sometimes confused with the lean right category resulting in the classifier accuracy of 90%.

Conclusion

In this paper, we proposed an automated infrared camera-based sedentary time monitoring method SVM classifier with SURF features. It is expected that this approach will have better classification accuracy than the accelerometer approach while keeping the individual's identity safe. The paper introduces a viable automated sedentary posture detection method that can be implemented to improve healthy office environment.

References:

[1] "Physical activity and sedentary leisure time and their associations with BMI, waist circumference, and percentage body fat in 0.5 million adults: the China Kadoorie Biobank study," The American journal of clinical nutrition, vol. 97, no. 3, pp. 487-496, 2013.

[2] E. Banks, L. Jorm, K. Rogers, M. Clements, and A. Bauman, "Screen-time, obesity, ageing and disability: findings from 91 266 participants in the 45 and Up Study," Public health nutrition, vol. 14, no. 1, pp. 34-43, 2011.

[3] G. Lyons, K. Culhane, D. Hilton, P. Grace, and D. Lyons, "A description of an accelerometer-based mobility monitoring technique," Medical engineering & physics, vol. 27, no. 6, pp. 497-504, 2005.

[4] F. Cirillo, "The pomodoro technique (the pomodoro)," Agile Processes in Software Engineering and, vol. 54, no. 2, 2006.

[5] Bay, Herbert, Tinne Tuytelaars, and Luc Van Gool. "Surf: Speeded up robust features." European conference on computer vision. Springer, Berlin, Heidelberg, 2006.

[6] O'Hara, Stephen, and Bruce A. Draper. "Introduction to the bag of features paradigm for image classification and retrieval." arXiv preprint arXiv:1101.3354 (2011).