Infrared Physics & Technology 73 (2015) 149–157

Contents lists available at ScienceDirect

Infrared Physics & Technology

journal homepage: www.elsevier.com/locate/infrared

Automatic classification of thermal patterns in diabetic foot based on morphological pattern spectrum

D. Hernandez-Contreras, H. Peregrina-Barreto, J. Rangel-Magdaleno *, J. Ramirez-Cortes, F. Renero-Carrillo

National Institute for Astrophysics, Optics and Electronics, Luis Enrique Erro No. 1, Puebla, Mexico

HIGHLIGHTS

- Thermograms foot analysis to prevent diabetic foot complications.
- Temperature pattern for control and diabetic groups.
- Non-linear classification using artificial neural networks.
- Feature vector based on morphological pattern spectrum.

ARTICLE INFO

Article history:
Received 25 June 2015
Available online 28 September 2015

Keywords:
Thermography
Artificial neural network
Pattern spectrum
Diabetes mellitus
Diabetic foot

ABSTRACT

This paper presents a novel approach to characterize and identify patterns of temperature in thermographic images of the human foot plant in support of early diagnosis and follow-up of diabetic patients. Composed feature vectors based on 3D morphological pattern spectrum (pecstrum) and relative position, allow the system to quantitatively characterize and discriminate non-diabetic (control) and diabetic (DM) groups. Non-linear classification using neural networks is used for that purpose. A classification rate of 94.33% in average was obtained with the composed feature extraction process proposed in this paper. Performance evaluation and obtained results are presented.

1. Introduction

Diabetes Mellitus (DM) is a chronic and complex disease that requires continuous and early medical care to prevent further complications [1]. Globally, it is estimated that there are about 382 million people with diabetes, and the number of people with this disease will increase by more than 592 million in less than 25 years [2]. Diabetic foot ulcers are one of the major complications experienced by diabetic patients and if it is not treated in time there can be risk of amputation [3]. Therefore, the analysis of temperature distribution in the plantar region can be useful for early diagnosis of these complications. The infrared thermography is a noninvasive and noncontact technique, which is a very useful option in medical applications [4–6]. With this technique a complete representation of temperature distribution in the plantar region can be obtained. This representation reveals information associated to damages in circulatory flow typically present in DM.

In recent years, there have been several studies to relate the plantar region temperature with some complications of diabetic foot. In [7], a study to define the relation between foot temperature and diabetic neuropathy is presented. In this study, patients were chosen randomly with the only criteria that they do not have foot problems such as ulcers, infections and amputations. The results indicated that patients with diabetic neuropathy showed a higher temperature in the foot (32–35 °C) compared to patients without neuropathy (27–30 °C). Also patients with neuropathy had a higher Mean Foot Temperature (MFT). In [8], it is reported a quantitative information about the temperature difference, their distribution and area inside of the four main regions (angiosomes) of the foot proposed by Attinger [9]. In 2010, Nagase et al. [10] proposed the first study which try to find temperature patterns in the plantar region. Based on this temperature patterns, they proposed a novel classification system with 20 different categories of plantar thermographic patterns, according to the 4 plantar angiosomes. However, they concluded that this classification is too complicated to use in daily situations. Mori et al. [11] proposed a new pattern classification by a computer-based system, but they concluded that the results found were similar to those obtained in the research made by Nagase [10]. In non linear classification tasks, artificial neural

* Corresponding author.
E-mail addresses: jjrangel@ieee.org, jose.rangel.magdaleno@gmail.com (J. Rangel-Magdaleno).

http://dx.doi.org/10.1016/j.infrared.2015.09.022
1350-4495/

networks (ANN) have demonstrated to be a useful tool. The use of ANN in medicine is not new, and among its applications we can find classification of medical images [12], disease detection based on image processing [13], segmentation and detection edges in medical images [14–16], among others. In this paper, the morphological pattern spectrum is used as a tool to create different feature vectors. This technique has been used in different works for feature extraction [17–20], because it gives us information about the shape and size of the objects in the image, with very good properties of translation and rotation invariance. In [17], it is presented a novel feature-extraction method based on the morphological pattern spectrum for a biometric shape-based hand recognition system and this is tested using a Euclidean distance classifier. In [18], it is presented an automatic leukocyte classification based on mathematical morphology to create a feature vector which was tested using 4 different classifiers, obtaining the best results with ANN. These examples indicate the relevance of the morphological pattern spectrum for feature extraction and also the relevance of the ANN in pattern recognition problems arising in the vast field of medical applications.

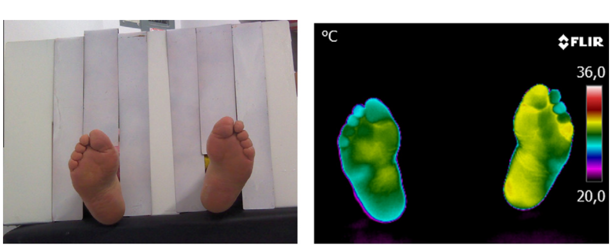
In this paper, a novel classification system to identify temperature patterns associated to healthy and diabetic patients is presented. The classification system will consist of 4 steps: plantar region segmentation, hottest area segmentation, and characterization of the hottest area and classification of the thermal pattern. In this study, we propose the use of an ANN for automatic classification.

This paper is organized as follow. In Section 2 basic concepts are presented. In Section 3, we describe feature vector extraction, test, and ANN classification performance. Concluding remarks of this work are discussed in Section 4.

2. Methodology

2.1. Thermograms acquisition and participant information

In this paper, we use 44 thermograms (24 non diabetic patients and 20 with diagnosed diabetes) reported in previous work [21], plus 16 extra thermograms (6 non diabetic patients and 10 with diagnosed diabetes). For thermograms acquisition, the recommendations of the International Academy of Clinical Thermology Standards and Protocols (http://www.iact-org.org/) were followed. Thermograms are captured with the subject in supine position in a room at controlled temperature of 20 ± 1 °C. The proper preparation of the subject consists of requesting him/her to remove his/her shoes and socks and clean his/her feet with a damp towel. After that, the subject was invited to maintain a supine position for 15 min. An obstructive IR device is placed to isolate the temperature foot of the rest of the body. For the extra thermograms, several modifications were made to the obstructive IR device which allowed us to have a better contrast between plantar region (PR) and background. Fig. 1 shows the obstructive IR device and a thermogram example. The images were captured with an infrared camera FLIR E60 with a thermogram resolution of 320×240 pixels.



(a) (b)

Fig. 1. (a) Obstructive IR device, (b) example of a thermogram taken with the new obstructive IR device.

In this paper we consider two groups: control group (non diabetic patients) and DM group (subjects with diagnostic of DM). Both groups are composed of 30 volunteers including men and women aged between 20 and 70 years. In both groups, information about first-degree relatives (FDR) and second degree relatives (SDR) with DM was collected. Also volunteers of DM group were asked about the duration of this condition (see Table 1). Diabetic patients with amputation, ulcers or infections were excluded from this study.

2.2. Grayscale characterization

The thermal images are represented in the RGB color space associated with a color palette and a scale ranging from 20 to 36 °C. With the help of FLIR R&D software we can convert this image to a graylevel palette where white represents the maximum temperature and black represent the minimum. This palette has values ranging from 0 to 255, divided into 32 segments or classes, with a resolution of 0.5 °C. The background corresponds to the obstructive IR device which is colder than the PR and its temperature is out of the considered range of values.

2.3. Foot segmentation

Previous works have suggested that abnormal variations in temperature could be useful to detect high-risk areas [22,23]. Chan et al. [24] designated as Butterfly Pattern to the temperature distribution in a normal subject. In such distribution, the arch presents the highest temperature, while the lowest temperature is in the toes. By a qualitative evaluation, we found that this distribution changes in the DM group, presenting high temperatures in different regions of the foot, so the analysis in this paper will focus only on the areas with the highest temperature, because these areas can help to identify patterns of high-risk. Therefore, before performing the corresponding analysis we need to isolate the highest temperature areas of the PR. The first step is to segment the PR of the rest of the background and to divide each thermogram in two separate images, one for each foot. One of the problems with the obstructive IR device mentioned in the previous work [21] is that it does not isolate completely the PR of the rest of the body, and we may see temperature regions that do not belong to the sole. On the other hand, if the temperature in the PR is low, it could be confused with the rest of the background, losing part of the foot when an automatic segmentation is performed. For both problems several modifications were made to the obstructive IR device getting high contrast which allows automatically segmentation of PR in the thermogram. With these modifications we can ensure that the contrast difference between PR and background will be higher. The simplest way to automatically segment this region is by thresholding. The thresholding is the most common pixel-based method to segment an image [25,26]. This method allows us to convert our grayscale image to binary image. To define the threshold, we

Table 1
Demographic information of both groups (mean ± standard deviation).

	Control group	DM group
Volunteers	30	30
Female	14 (46.67%)	18 (60%)
Male	16 (53.33%)	12 (40%)
Age (years)	38.28 ± 11.56	57.14 ± 10.03
DM duration (years)	–	11.09 ± 6.93
Volunteers with FDR and SDR with DM	19 (63.33%)	25 (83.33%)