Measuring Plantar Temperature Changes in Thermal Images Using Basic Statistical Descriptors

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Abstract. One of the principal complications of patients that suffer from Diabetes Mellitus (DM) and that can lead to ulceration is the Diabetic foot. As tissue inflammation causes temperature variation, several studies show that thermography can be used to detect complications in diabetic foot and help predicting the risk of ulceration. It is known that, although healthy individuals present characteristic plantar temperature variation patterns, the same does not happen with diabetic patients, for which a particular pattern can not be found; thus, making the measurement of the temperature variation more difficult. Given that, it is important to research in this field in order to obtain methods that can detect atypical variations of the temperature in the sole of the foot. With this in mind, the objective of this work is to present a methodology to analyze the distribution of temperature in thermograms of the foot's plant and classify it as belonging to a DM individual with risk of ulceration or a healthy individual. After foot partitioning with a clustering algorithm, basic statistical descriptors are computed for each cluster. A binary classifier to predict the risk of ulceration in the diabetic foot was evaluated with the different descriptors; both a quantitative temperature index and a classification threshold are calculated for each descriptor. To evaluate the performance of the classifier, experiments were conducted using a public dataset (containing 45 thermograms of healthy individuals and 122 images of DM ones); the following metrics were obtained: Accuracy = 78%, AUC = 86% and F-measure = 84%, with the best descriptor.

Keywords: K-means · Descriptors · Classification · Diabetic foot · Thermogram

1 Introduction

Diabetes Mellitus (DM) is a chronic disease that affects many people and causes many deaths. In 2017, approximately 3.2 to 5.0 million deaths were associated with this disease [1].

DM individuals frequently develop a pathology, named Diabetic foot (DF), that is characterized by a variety of foot injuries, like ulceration and/or destruction of deep

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tissues that can be related with neuropathy or vascular disease [2]. The development of ulcers can cause infections, that, when severe, may lead to limb amputation [3]. DF problems are directly linked to abnormal changes of the temperature in the plantar region; thus, justifying the temperature monitoring and the identification of characteristic patterns as well as the measurement of thermal changes. A specific spatial temperature pattern, called butterfly pattern, can be found in the feet of healthy individuals, while, in the groups of the diabetic patients an extensive diversity of spatial patterns can be detected [4–6].

Infrared thermography (IRT) is a non-contact, non-invasive and fast method that permits to observe the distribution of the temperature of the sole of the foot and to analyze the thermal alterations that take place [7].

The use of IRT to automatically identify a foot as belonging to a diabetic individual captured the attention of a number of researchers for some time now, for example [4–11]. As the foot does not have an uniform temperature, it is of significance to consider a partition of the foot in regions, in order to obtain more detailed information concerning temperature variation, in addition to the analysis of the temperature of the entire foot [12]. Some authors present a thermal analysis based on the observation of specific points, or specific regions. For example, in [13, 14], 33 regions were considered, considering the points of the foot that are most likely to ulcer. Another approach that has been quite used and discussed recently [4–6, 15, 16] splits the plant of the foot in four areas and it is based on the concept of angiosome (region of tissue which has blood supply through a single artery); its use is justified by the fact that the reduction in blood supply is one of the leading causes of DF ulceration.

Additionally, only a few studies on this topic propose quantitative information to estimate the plantar temperature variation; for example, in [15] the temperature difference of the matching regions of the right and left foot are considered, while in [4], an index involving both the temperature difference between the regions and the temperature interval of the control group (constituted of healthy individuals) is computed.

In [17] a quantitative index based on the average values of the temperature in clusters regions was presented. The present work is a sequel of the one in [17], where a clustering algorithm was used to split the foot in regions and the average temperature descriptor is used to predict diabetic foot.

In this work, a method that analyzes thermographic photos of the plant of the foot and gives a quantitative temperature index is proposed. To obtain the quantitative temperature index, each foot is divided into clusters and a statistical descriptor measure of the temperature of each cluster is considered. The index measures the temperature deviations in respect to the control group allowing to classify the foot in one of the categories *risk of ulceration* or *healthy*. The final stage of the method implements a binary classifier by thresholding the quantitative temperature index with the optimum threshold that separates the two classes.

A clustering method groups similar values of the temperature in a cluster; therefore, isolating the different areas (clusters) of the foot that present approximate temperature values [18], being the range of temperatures within each one of the clusters low; thus, it is expected to obtain an index capable of measuring thermal variations in respect to

the control group. Notice that a lower value index is obtained when low variation of temperature values occur within the same region.

In this article, the k-means algorithm is used to obtain the clusters. Moreover, two new temperature descriptors are calculated in the regions found by the clustering algorithm. Using the new proposed descriptors, two new indexes, called minimum cluster temperature index and maximum cluster temperature index, are computed.

To measure the classifiers' performance, experiments using a public database [12] were performed, being the performance metrics Accuracy, Area Under the Curve, F-measure, Precision, Sensitivity and Specificity used to assess and validate the presented classification method. Furthermore, the average cluster temperature index, presented in [17], was compared with the two new indices implemented in this work; a generalized improvement in the evaluation metrics could be observed when the minimum cluster temperature index was used to classify the thermographic images of the used public dataset.

This paper is organized as follows. In Sect. 2 the proposed method is described. In Sect. 3 the used data set is introduced and the obtained results are presented and analyzed. In Sect. 4 the conclusions and the guidelines for future work are presented.

2 Methodology

The proposed method has three phases of processing: temperature clustering, index computation and classification. In the first phase, a clustering algorithm divides the foot into five regions (clusters), based on the temperature values. In the second phase, for each cluster, regional descriptors of temperature are calculated (namely, average, standard deviation, maximum and minimum values), as well as an index concerning the variation of the temperature in respect to a reference value. Finally, applying a thresholding procedure on the index, the subject is classified in one of the classes: healthy or risk of ulceration.

2.1 Clustering

Clustering is an important technique for data mining, with applications ranging from statistics, computer science, biology to social sciences [18, 19].This technique consists of grouping data samples in groups based on a certain similarity measure, being a lot of clustering algorithms cited in the literature [20, 21]. The dataset is divided into groups so that data points in the same group are similar while data points in different groups are dissimilar to each other.

The most popular clustering algorithms are the centroid based, including K-means [22]; that is the algorithm used in the first phase of the presented method.

K-means is one of the most used clustering algorithms, with a straightforward implementation and being computationally efficient, even when applied on large datasets. The algorithm splits the original data into k non overlapping groups, defined as clusters of data points exhibiting similar properties. The number of clusters (k parameter) is specified by the user depending on the problem to be solved. The K-means algorithm through an iterative process converges to a solution where subsets of data points are assigned

into k clusters. The final cluster configuration is determined by the minimization of the sum of the distances of each data point to the cluster centroid, in all clusters.

The algorithm consists in two steps designated expectation-maximization. In the expectation step each observation is assigned to the nearest cluster centroid. In the next step, named as maximization, for each cluster the new centroid is determined by averaging the all data points belonging to the cluster. The algorithm proceeds as follows:

1. Specify the number of clusters, k, and randomly choose the initial centers (centroids).
2. **Repeat**
3. Each data point is assigned to the cluster with the closest centroid.
4. Compute the new centroid.
5. **Until** all the clusters centroid stop moving (k-means has converged).

One advantage of K-means is that it easily scales to large data set, as for example high resolution images. However, due to his non-deterministic characteristic, the algorithm can produce different cluster configurations from two separate runs even if the data points are the same. The final results strongly depend of the arbitrary selection of the initial centroid [22, 23]. Figure 1 shows the results of two runs of the K-means in the same dataset, which obtained different final configurations.

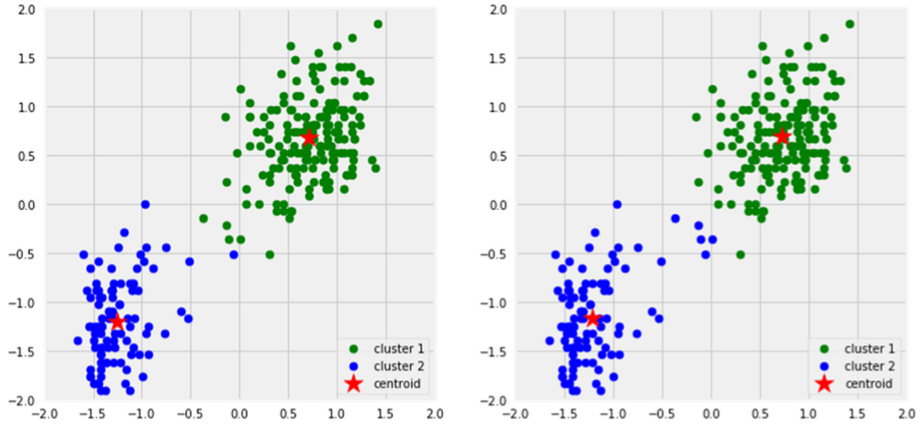

Fig. 1. Different cluster configurations in two runs of K-means in the same dataset.

2.2 Computation of Cluster Temperature Indexes

After the foot partition using K-means, each cluster can be described by a set of basic statistical descriptors, such as average, maximum, and minimum value of temperature. These descriptors extracted from each cluster can be used to estimate how much the foot temperature of an individual deviates from the reference temperature calculated in the control group, formed by healthy feet.

In this work we proposed new quantitative indexes to measure the foot temperature changes in respect to the control group. The statistical descriptors of each clusters are used to calculate three indexes named as Cluster Temperature Indexes (CTIs).

Each index is calculated as the average of the positive differences between the temperatures of an individual (IND) and the correspondent reference values ($\overline{CTR}$) obtained using the average of the data from the control group, as in (1), where $\overline{CTR}_i$ is the average value of the reference temperature descriptor for cluster i and IND_i is the value of the temperature descriptor of the individual (IND) in study for cluster i.

$$CTI = \frac{\sum_{i=1}^{5} \left| \overline{CTR}_i - IND_i \right|}{5} \tag{1}$$

When the average descriptor is used, the index in (1) will be called as Average CTI (ACTI); similarly, when the maximum and the minimum descriptors are considered the Maximum CTI (MCTI) or the minimum CTI (mCTI) are obtained from (1).

The value of each CTI index is an indicator of variations in the temperature pattern of a subject's foot in relation to the normal temperature pattern (butterfly pattern). It is expected that higher index values are related with greater values of temperature variation; therefore, flagging the subject as having higher risk of appearing of foot lesions. Thus, these indexes can be used to classify each foot as belonging to a healthy or a DM individual with risk of ulceration.

2.3 Classification

In the last stage of the method the thermograms are classified in one of the categories: *healthy* or *risk of ulceration*, based on the thresholding of the CTI values. The success of the classification depends on the selection of an optimum cluster threshold value (CTT - Cluster Temperature Threshold); for each descriptor a CTT is computed.

During the experiments several performance metrics were calculated: *Sensitivity* (Se), *Specificity* (Sp), *Precision*, *Accuracy*, *F-measure*, and *Area Under the Curve* (AUC), defined by (2) to (6), where TP, FP, TN and FN represent the number of cases of *True Positive*, *False Positive*, *True Negative* and *False Negative*, respectively:

$$Sensitivity = \frac{TP}{TP + FN} \tag{2}$$

$$Specificity = \frac{TN}{FP + TN} \tag{3}$$

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$Accuracy = \frac{TP + FN}{TP + TN + FP + FN} \tag{5}$$

$$F_{measure} = \frac{2{*}TP}{2{*}TP + FP + FN} \tag{6}$$

The Receiver Operating Characteristic (ROC) curve is a way to show in a graphic the connection between the true positive rate (sensitivity) and the false positive rate (1-specificity) for different cut-off (threshold) of CTI.

As the method is used to detect the risk of lesion, *sensitivity* and *specificity* are the most relevant metrics to assess the performance [24]. The balance between these two-performance metrics can be achieved if a cut-point is determined as the threshold to classify the foot as *healthy* or in *risk of ulceration*. The value was chosen using an approach known as the point closest-to-(0,1) corner in the ROC plane, which defines the optimal cut-point as the point that minimizes the Euclidean distance between the ROC curve and the (0,1) point, denominated as ER criteria [25]. In this criteria, the "optimal" cut-point is obtained using (7).

$$ER = \sqrt{(1 - Se)^2 + (1 - Sp)^2} \tag{7}$$

To summarize the entire location of the ROC curve the AUC is used, as it is an effective and combined measure of sensitivity and specificity that describes the inherent validity of diagnostic tests, rather than depending on a specific operating point [26].

3 Experimental Results

To evaluate the classifier, a public database that contains 334 individual plantar thermographic photos, of 167 individuals (being 45 of healthy subjects and 122 of DM individuals with risk of ulceration) [12]. All the computational experiences were carried out using version R2020b of the software MATLAB.

In this section the results of the classification using the clustering algorithm described in Sect. 2 are presented. It is important to notice that, as reported in [17], several experiments were carried out to determine the number of clusters that should be used in order to obtain the best classification, starting with three clusters and increasing this number until six. From these experiments it was possible to observe that better metric results are obtained with four clusters than with three and even better ones were obtained with five clusters, but the same does not happen when six clusters are considered; thus, it has been concluded that the best results were obtained when considering foot division in five clusters.

The classification indexes (1), are based on reference temperature values. For each descriptor, the reference average values of the temperature per cluster ($\overline{CTR}$) and the correspondent standard deviation (Std. dev.), both measured in Celsius degrees (ºC), as well as the reference CTI average values (ACTI, mCTI and MCTI) and correspondent standard deviation are presented in Table 1.

As the performance of the method depends on the threshold value used to determine whether the thermogram is from a healthy or a DM individual, various threshold values were tested, considering the reference CTI value obtained with each descriptor. In order to obtain a threshold that balances sensibility and sensitivity metrics, the ER measure approach was used. The value 1.9 was selected as the threshold to classify the thermogram as risk ulceration or healthy using the average descriptor, the value 1.84 was chosen when using the minimum and 2.22 was set for the maximum.

Table 1. Average and standard deviation of the temperature (ºC) for the control group, per cluster, after the k-means clustering, with different descriptors.

Descriptor	Cluster	1	2	3	4	5	CTI
Average	$\overline{CTR}$	23,93	25,52	26,59	27,61	28,88	1,23
	Std. dev	1,75	1,60	1,56	1,50	1,44	0,91
Minimum	$\overline{CTR}$	21,38	24,72	26,06	27,11	28,25	1,31
	Std. dev	2,07	1,66	1,58	1,52	1,46	0,79
Maximum	$\overline{CTR}$	24,71	26,05	27,10	28,25	29,80	1,31
	Std. dev	1,66	1,58	1,52	1,46	1,57	0,79

Analyzing the results obtained with the different descriptors, presented in Table 2, it can be observed that both the average and the maximum present similar metric results, but the maximum descriptor presents a more unbalanced sensibility and sensitivity. Furthermore, it can be concluded that the minimum is the descriptor that presents the best results, obtaining in some metrics, like F-measure or Accuracy an increase of 4% when compared with the algorithm that presents the worst metric results. To compare the performance of the classifiers (represented by the AUC metrics), the ROC curves and the CTT obtained for the three descriptors, are illustrated in Fig. 2.

Table 2. Metrics scores using K-means, for the 3 descriptors.

Descriptor	CTT	Accuracy	Se	Sp	Precision	AUC	F-measure	ER
AVERAGE	1,9	74%	73%	78%	90%	84%	81%	0,350
MIN	1,84	78%	77%	81%	92%	86%	84%	0,297
MAX	2,22	72%	66%	88%	94%	83%	77%	0,361

Observing Fig. 2 it is perceptible that, although all the AUC results are higher than 83%, the best results in classification, with the highest AUC values and best balance between sensibility and sensibility are obtained with the minimum descriptor.

In order to better illustrate the comparison between the used descriptors, in Table 3, information concerning three feet thermograms is presented. The first case is a thermogram from the control group, where the butterfly pattern is easily detected (CG005 from [12]), the second example was chosen to exemplify a case when the butterfly pattern is not so well defined (DM051 from [12]), and, finally, in the third case a thermogram of a foot that can clearly be characterized as belonging to a DM individual was chosen (DM010 from [12]). Additionally, the columns of Table 3 contain information concerning: the subject's identification (Subject), the thermographic image (Thermal), the

image obtained after k-means clustering (K-means), the index value for each descriptor (ACTI, mCTI and MCTI), as well as the measures identification (Measures) and the corresponding values for the entire foot (General).

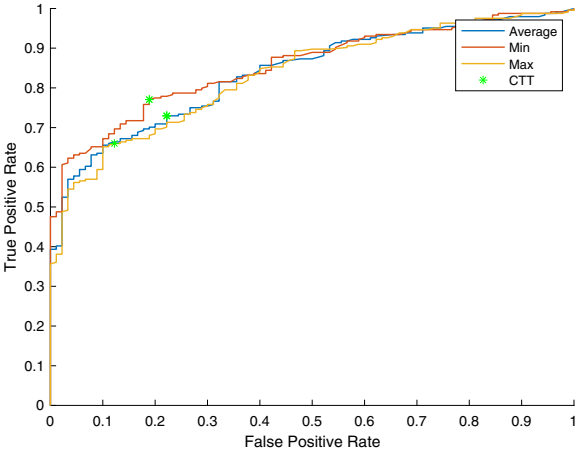

Fig. 2. ROC curves for all the three descriptors.

Table 3. CTI's and temperature measure values, per cluster, for some feet thermograms of the control and the DM groups in [12].

Subject	Thermal	K-means	ACTI	mCTI	MCTI	Measures	General
CG005			0,24	0,50	0,20	Min	22,94
						Max	29,90
						Average	26,75
						Std dev	1,64
DM051			1,62	2,15	1,34	Min	25,65
						Max	30,04
						Average	28,49
						Std dev	0,75
DM010			7,50	7,76	7,13	Min	30,26
						Max	35,58
						Average	34,31
						Std dev	0,61

The thermal analysis of the feet allowed to observed that, when the average temperature values of the clusters of a foot are close to the ones of the control reference (Table 1),

low values of the CTI's are obtained and the foot distribution temperature approximates the butterfly pattern, typical of non-diabetic subjects, as can be observed in the thermogram of subject CG005 (Table 3). Generally, the method classifies accurately these type of feet for all the descriptors.

Thermal changes in the feet of the diabetic subjects can vary from marginally dissimilar from the butterfly pattern to a totally diverse pattern. This fact reflects in the CTI's value, being that, wide variations of the CTI indexes' values can be observed. As shown in Table 3, when minor temperature deviations occur, the CTI's values are closer to the reference CTI's values, as in DM051 (Table 3). In this case, it appears that when using the average and the maximum descriptors, the obtained CTI's shows more difficulty in classify the foot as belonging to a healthy or a diabetic individual. On the other hand, it seems that when using the minimum descriptor, the method is able to find the small thermal changes, showing a pattern marginally dissimilar from the butterfly pattern and that correspond to the transition between the two classes; thus, leading to a better performance of the classifier for these type of feet than the one obtained when using the other two descriptors.

As variations start to be more accentuated, the CTI's values increase, moving further away from the reference CTI's values. Additionally, it can also be observed that, when the hot spots evolve, they not only become wider, but also warmer; thus, higher CTI's values are achieved. The hot spots may even cover the entire plantar region, reaching very high temperature values and presenting very high CTI's values, as in DM010 (Table 3). In general, and similarly to what happens with the first group of feet, this method classifies accurately these type of feet for all the descriptors.

4 Conclusions

In this work, a method that uses thermographic photos of the sole of the foot to analyze the multiplicity of thermal changes in the plantar region, is presented. In this approach, the clustering concept is used to obtain different descriptors and, for each one, a quantitative temperature index and a classification temperature threshold are obtained. In the classification stage, for each descriptor the optimum threshold value was set finding a balance between the sensitivity and specificity metrics.

According to the presented results, the method proved to be effective in helping to measure temperature variations in the plant of the feet, and the obtained indexes can detect these changes, being that a higher value of the index corresponds to greater values of temperature variation. Additionally, the determined thresholds allow to classify an individual as having risk of ulceration or being healthy.

When comparing the different descriptors, it can be noticed that, in general, the presented method is able to correctly classify the feet, for all the descriptors, when the temperature distribution of the plant of the foot preserves the butterfly pattern, or when the hot spots are visible and may, even, cover the entire plantar area and reach high temperature values. On the other hand, using the minimum descriptor, the method is able to find small thermal changes, which are slightly different from the butterfly pattern and correspond to the transition between the two classes. Therefore, it can be concluded that the classifier's performance using the minimum descriptor surpasses the one obtained by the classifier when using the other two descriptors.

With this work, another step is taken in order to obtain an effective classification tool that can assist in medical diagnosis, thus, helping in the prevention of ulcerations and in the early detection of the risk of injuries.

As future work it is intended to balance the number of the photos of diabetic and healthy and DM subjects, by extending the dataset.

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