A Robust Footprint Detection Using Color Images and Neural Networks

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Abstract. The automatic detection of different foot's diseases requires the analysis of a footprint, obtained from a digital image of the sole. This paper shows that optical monochromatic images are not suitable for footprint segmentation purposes, while color images provide enough information for carrying out an efficient segmentation. It is shown that a multiplayer perceptron trained with bayesian regularization backpropagation allows to adequately classify the pixels on the color image of the footprint and in this way, to segment the footprint without fingers. The footprint is improved by using a classical smoothing filter, and segmented by performing erosion and dilation operations. This result is very important for the development of a low cost system designed to diagnose pathologies related to the footprint form.

1 Introduction

When the foot is planted, not all the sole is in contact with the ground. The footprint is the surface of the foot in contact with the ground. The characteristic form and zones of the footprint are shown in figure 1(a). Zones 1, 2 and 3 correspond to regions in contact with the surface when the foot is planted; these are called anterior heel, posterior heel and isthmus respectively. Zone 4 does not form part of the surface in contact and is called footprint vault [18]. These footprints play a key role in the detection of different foot's diseases.

The sole image can be acquired either in gray scale or color format. The segmentation of gray scale images can be done using standard techniques [7]. However, there are some problems with the segmentation of gray scale images produced by shadows, surface curvature and metamerism [21]. Taking in account the previous problems, segmentation techniques in color images have been developed. There are studies where the operators for edge detection have been extended from gray scales to color images [3], [8]. In other cases, segmentation techniques based on neural networks and statistical classifiers have been developed [1]. Good reviews of segmentation techniques based on color images can be found in [4] and [5].

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Among segmentation methods relevant for this study is the use of neural networks. In particular, the multilayer perceptron (MLP) and the training algorithm called backpropagation [9] have been successfully used in classification and functional approximation. An important characteristic of MLP is its capacity to classify patterns grouped in classes not linearly separable. Besides that, it has been shown that a one-hidden-layer perceptron (or two-layer perceptron) is an universal function estimator [19].

The first disadvantage of the backpropagation algorithm is its speed of convergence, this has led to the use of more sophisticated optimization methods. A good summary of these optimization methods is found in [13], and the application of such methods to the training of neural networks can be found in [17].

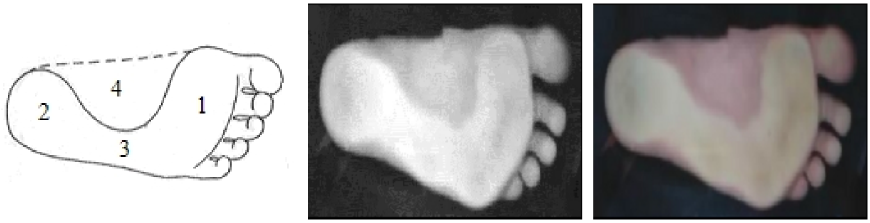
A second disadvantage of MLP trained with error backpropagation is that it may classify by mistake patterns not participating in the training process; i.e. it lacks of generalization. Generalization means that the neural network correctly classifies unknown patterns.

A technique to improve the generalization is called regularization, and consists in building a cost function from the sum of a function for error measurement (typically the average quadratic error) and a function representing the network complexity. Different regularization methods propose different functions for representing the network complexity, as example: weight decay [6], weight elimination[11] and approximate smoother [22]. A current technique is the bayesian regularization, which uses the weight decay as the cost function, the Levenberg-Marquardt optimization algorithm [10], and a bayesian approach for defining the regularization parameters [2]. Among the advantages of the bayesian regularization technique are: (1) by using the Levenberg-Marquardt optimization algorithm, the speed of the learning process is improved, and (2) it provided the effective parameters the network is using. By using the network effective parameters, it is possible to define the amount of neurons in the hidden layer according to the procedure described in [10].

The data set used in this work, containing more than 200 images, was obtained using a prototype designed and built to capture sole images. Matlab, the Image Processing Toolbox and the Neural Networks Toolbox were used as platform for carrying out most of data processing work. The structure of this paper is as follows. Section 2 describes the problem of capturing footprints using gray scale images, shows the footprint segmentation using color images and neural networks, and describes the segmentation improvements. Section 3 shows a quality measurement of the footprint segmentation. Finally, Section 4 provides some conclusions.

2 Footprint Segmentation Using Color Images and Neural Networks

A first attempt to solve the segmentation problem considered gray scale images, since the use of this type of image allows the use of simple algorithms for its



(a) Zones of the sole (b) Gray level image (c) Color image

Fig. 1. Images of the sole

segmentation. Figure 1(b) shows a gray-scale footprint image. It can be seen at first sight that there are patterns of the vault of the foot which have the same level of gray as others of the posterior heel. This means that different regions reflect the same amount of light (i.e. having the same gray values, whereas being differently colored), this phenomenon is known as metamerism [21]. Thus, for this application, a segmentation based on gray scale is not adequate to separate the pixels of the footprint from the rest of the image by a simple threshold method.

Because of the metamerism problem in gray scale images, the use of color images is proposed. Color model means the specification of a system of three-dimensional coordinates and a subspace of this system in which every color is represented by only one point [7]. The RGB color model has been used in this study. Figure 1(c) shows a color footprint image.

This work proposes the use of NN for footprint segmentation. The network acts as a pixel classifier [1],[15], and by the training process, it learns the pixel classes of the training set. In addition, by its generalization capabilities, it can also adequately classify pixels from the same image but not belonging to the training set and also pixels belonging to other images.

The neural network has three inputs corresponding to the RGB coordinates of the particular color. In the color footprint image in figure 1(c) it is clearly shown the existence of 3 pixel classes: the one from the image background, the one from the vault, and the one from the footprint. The network has an output assuming the value 1 for background pixels, 0 for the footprint, and -1 for the vault. The training set considers 709 samples selected from just one image, the 26% correspond to the background, 38% to the vault and 36% to the footprint. The size of each sample image is 434x342 pixels. The training of the multi-layer perceptron has the following characteristics:

- A hidden-layer MLP was used.
- Number of inputs: 3.
- Number of outputs: 1.
- A bayesian regularization backpropagation as training algorithm.
- Learning in batch modality, where weights are updated at the end of each stage.

Table 1. Determining the amount of neurons in the hidden layer for the footprint segmentation by using MLP

NNCO	Epochs	SSE	SSW	Effective parameters	Total parameters
1	142/3000	130.657/0.001	55.7698	3.14e+000	6
2	45/3000	0.00029/0.001	8221.40	1.09e+001	11
3	18/3000	0.00067/0.001	6425.98	1.44e+001	16
4	36/3000	0.00048/0.001	7446.65	1.93e+001	21
5	125/3000	0.00064/0.001	3680.94	2.33e+001	26
6	66/3000	0.00073/0.001	3023.94	2.76e+001	31
7	113/3000	0.00080/0.001	3267.58	3.31e+001	36
8	329/3000	0.00091/0.001	3047.76	3.65e+001	41
9	104/3000	0.00098/0.001	2636.46	4.00e+001	46
10	150/3000	0.00097/0.001	2790.33	4.31e+001	51
11	140/3000	0.00079/0.001	2618.23	4.77e+001	56
12	292/3000	0.00099/0.001	2272.81	4.90e+001	61
13	194/3000	0.00096/0.001	2269.79	5.52e+001	66
14	218/3000	0.00090/0.001	2327.66	5.85e+001	71
15	182/3000	0.00099/0.001	2325.35	5.51e+001	76
16	225/3000	0.00093/0.001	2287.15	5.96e+001	81
30	261/3000	0.00099/0.001	2212.30	5.94e+001	151

– The initial network weights were generated by the Nguyen-Widrow method [12] because it increases the convergence speed of the training algorithm [10].
– The initial regularization parameters a and b were 0 and 1 respectively.
– Successive trainings were done increasing progressively the amount of neurons in the hidden layer.

To determine the amount of neurons of the hidden layer, the procedure described in [10] was used. The details of this procedure are shown in table 1, where NNCO corresponds to the number of neurons in the hidden layer, SEE is the sum of the quadratic errors and SSW is the sum of the weight squares.

From the previous table it can be seen that from 13 neurons in the hidden layer, the SSE, SSW and the effective parameters stay practically constants. As a result, 13 neurons are considered in that layer. The evolution of SSE, SSW and the effective parameters are shown in figure 2. Figure 3 shows the classification results. The classification errors in the footprint edge can be improved by carefully choosing with more detail the training set in this zone.

Because the detection of pathologies related to the footprint shape requires the capture of the footprint without toes, the previous result is improved by smoothing the footprint and by eliminating the toes.

The improvement steps are the following: (1) binarization, (2) footprint erosion in order to disconnect the toes if it is necessary, (3) smoothing of the footprint by median filter or a low pass filter in the frequency domain, (4) discharging the toes by ticketing and segmentation by size, and (5) image dilation in order to recover the size. The techniques previously noted are described in [7]. To visualize the improvements, the binarization is shown in figure 4(a), erosion is

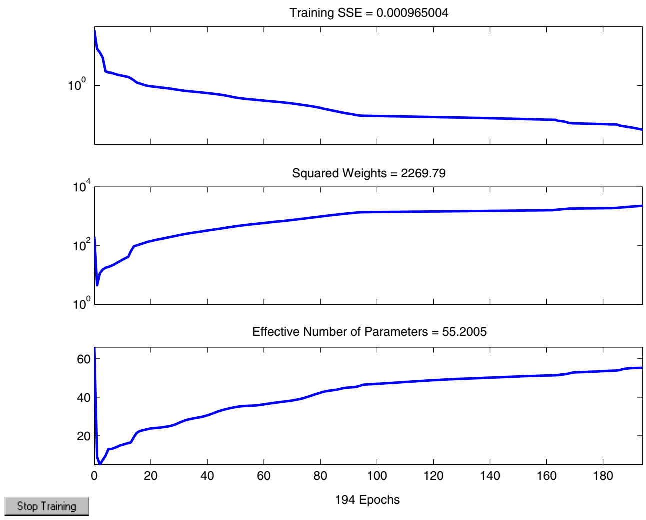


Fig. 2. MLP training

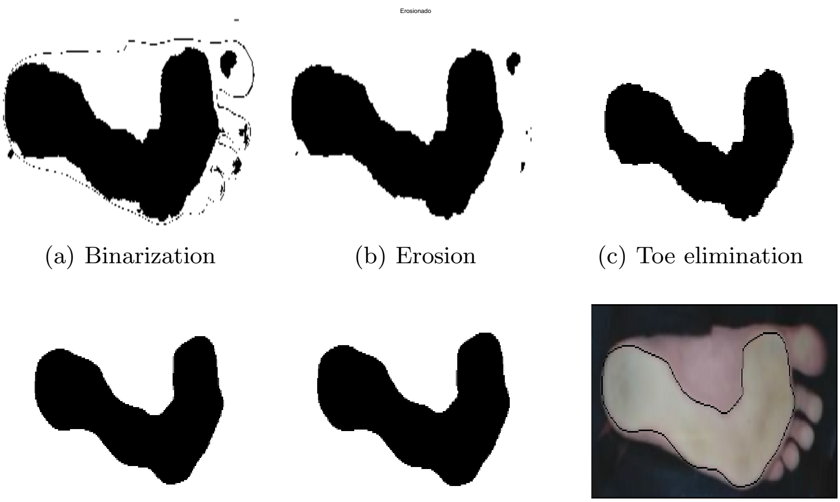
Fig. 3. Sole image classification

shown in figure 4(b), toe elimination is shown in figure 4(c), smoothing is shown in figure 4(d), dilation in figure 4(e), and the final result of the surrounding over the color image in figure 4(f).

3 Quality Assessment of the Footprint Segmentation

In the literature there are few methods to assess the quality of segmentation [14],[20], because the main reference is the one done by the human brain. Hence it is common in segmentation problems to compare the results obtained by the proposed algorithm with the human segmentation [15].

In order to assess the quality of the segmentation carried out by the MLP, a human-assisted segmentation was carried out for 10 footprint images and they are compared with the ones obtained by MLP. The results of such comparison are given in table 2, also the human segmentation of the footprint, the segmen-



(a) Binarization (b) Erosion (c) Toe elimination

(d) Smoothing (e) Dilation (f) Final edge

Fig. 4. Improvements in the footprint segmentation

Table 2. Quality assessment of the segmentation

N	Size of images	Different colors	Pixels bad classified	Percent pixels good classified
1	324x139	12518	1827	95,94
2	260x112	8741	1000	96,56
3	260x115	8567	1335	95,46
4	268x121	10008	1304	95,97
5	280x118	10626	1029	96,87
6	300x138	13062	1515	96,34
7	280x118	7586	1005	96,96
8	264x113	9903	709	97,62
9	260x118	8244	1335	95,58
10	294x124	10492	1337	96,25

tation done by MLP and its errors are shown respectively in figures 5(a), 5(b) and 5(c). The figures show that the classification errors are concentrated in the borders. It must be noted that the footprint edges are not well defined and there is a small transition zone, where it is not possible to have a perfect human segmentation. It is possible to improve these results by using a training set with more samples corresponding to the edge zone. It is important to remark that the error introduced by the presence of toes is completely eliminated by the process described in the previous section.

(a) Manual segmentation (b) MLP segmentation (c) Segmentation error

Fig. 5. Segmentation quality

4 Conclusions

This work has illustrated that the footprint segmentation using gray scales is not possible due to the problem known as metamerism, and the use of color image is then required.

The multilayer perceptron trained with bayesian regularization backpropagation not only enables to learn a training set representing the task of pixels classification but also to classify adequately pixels of other images.

Future work will consider a comparative study among different automatic segmentation algorithms, such as: non-parametric and non-supervised statistical classifier [23], self-organized neural networks [16], and the use of techniques for edge detection in color images [3],[8].

The results of this study are promising and they have established a very simple and fast method for footprint automatic detection with no toes. It is foreseen on the near future the development of an automatic and real time diagnosis system of pathologies related with the footprint shape.

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