Abstract—Nailfold capillaroscopy (NC) is a non-invasive imaging technique employed to assess the condition of blood capillaries in the nailfold and is particularly useful for diagnosis of scleroderma spectrum disorders and Raynaud’s phenomenon. Diagnosis is based on the identification of particular scleroderma patterns in the images which are typically grouped into early, active and late patterns. In this paper, we present a computer vision approach to recognizing scleroderma patterns in NC images. Following a pre-processing step to enhance image quality, we extract texture information in a holistic way rather than trying to extract and measure individual capillaries. As texture features we employ multi-dimensional LBP variance descriptors which capture multi-resolution texture and local contrast information. Our experimental results confirm our approach to work well and to outperform an earlier approach.

Keywords: Medical imaging, nailfold capillaroscopy, texture, LBP, MD-LBPV.

1. Introduction

Nailfold capillaroscopy (NC) is a non-invasive imaging technique employed to assess the condition of blood capillaries in the nailfold. It is particularly useful for early detection of scleroderma spectrum disorders [1] and evaluation of Raynaud’s phenomenon [2]. Diagnosis using NC images involves the classification into Early, Active and Late groups, also known as NC patterns or scleroderma (SD) patterns [3], [4] (see Fig. 1 for example images) based on the identification of enlarged or giant capillaries, haemorrhages, loss of capillaries, disorganisation of the vascular array, and ramified/bushy capillaries in the images [5].

While diagnosis based on NC is typically performed by manual inspection, computerised nailfold capillaroscopy can help to reduce the inherent ambiguity in human judgement while greatly reducing the time for diagnosis [6]. However, unfortunately the literature on computer aided approaches to NC image analysis is relatively sparse. Existing approaches [7], [8], [9], [10], [11] typically aim to segment capillaries and analyse the extracted structures.

In contrast, in [12] we have proposed a novel holistic approach for analysing NC images using texture analysis. In particular, we have shown that local binary pattern variance (LBPV) [13] texture features can be successfully employed to distinguish between different NC patterns. In this paper, we build upon this approach and show that by extracting these features in a multi-scale fashion while at the same time maintaining information between the scales, improved recognition performance can be achieved.

2. Scleroderma Patterns

In healthy subjects, the capillaries observed at the nailfold are fairly homogeneous in terms of size and shape and are regularly arranged. However, in patients with scleroderma as well as some other connective tissue diseases, abnormalities manifest themselves which can be identified using nailfold capillaroscopy.

The degree of these abnormalities indicates the severity and progression of the disease. Three NC patterns can be defined and characterised by [4]:

- Early (E): few giant capillaries, few capillary haemorrhages, relatively well preserved capillary distribution, no evident loss of capillaries.
- Active (A): frequent giant capillaries, frequent capillary haemorrhages, moderate loss of capillaries with some avascular areas, mild disorganisation of the capillary architecture, absent or some ramified capillaries.
- Late (L): irregular enlargement of the capillaries, few or absent giant capillaries, absence of haemorrhages, severe loss of capillaries with large avascular areas, severe disorganisation of the normal capillary array, frequent ramified/bushy capillaries.

3. Multi-dimensional LBPV Texture Features

3.1 Local binary patterns

Local binary patterns (LBP) are simple yet effective texture descriptors. The original LBP variant [14] operates on a per-pixel basis, and describes the 8-neighbourhood pattern of a pixel in binary form. If \( \{ g_1, g_2, \ldots, g_8 \} \) is the set of 8-neighbourhood pixels of a centre pixel \( g_c \), then the neighbouring pixels are set to 0 and 1 respectively by thresholding them with the centre pixel value. An LBP
The contrast in an image
\[
\text{VAR}_{P,R} = \frac{1}{P} \sum_{p=0}^{P-1} (g_p - \mu)^2
\]
(3)
with \(\mu = \frac{1}{P} \sum_{p=0}^{P-1} g_p\) can be incorporated with \(LBP_{P,R}\) to generate a joint distribution of \(LBP_{P,R}/\text{VAR}_{P,R}\) which gives a powerful texture descriptor as it contains both local pattern and local contrast information. An alternative is the use of a hybrid scheme, LBP variance (LBPV) [13], which also captures joint LBP and contrast information but where the variance \(\text{VAR}_{P,R}\) is used as an adaptive weight to adjust the contribution of the LBP code in histogram calculation.

LBPV histograms are calculated as
\[
LBPV_{P,R}(k) = \sum_{i=1}^{N} \sum_{j=1}^{M} \omega(LBP_{P,R}(i,j), k),
\]
(4)
with
\[
\omega(LBP_{P,R}(i,j), k) = \begin{cases} \text{VAR}_{P,R}(i,j) & \text{if } LBP_{P,R}(i,j) = k, \\ 0 & \text{otherwise} \end{cases}
\]
(5)
and \(k \in [0, K]\) defining the various LBP codes.
3.3 Multi-dimensional LBPV

By using several radii around a pixel, multiple concentric neighbourhood LBP codes can be extracted [15]. Such multi-resolution LBP features provide powerful texture descriptors. Clearly, this principle can also be applied to LBPV. In fact, in [16], multi-resolution LBPV was shown to give the best classification results on texture datasets captured under varying rotation and varying illumination and to outperform more than 30 other LBP-based texture features.

When recording multi-resolution texture information using LBPV, a histogram is generated for each scale/radius, while the histograms are concatenated to form a one-dimensional feature vector. In [17], it was shown that storing multi-scale LBP features in such a fashion leads to a loss of information between the different scales and added ambiguity. The joint distribution of LBP codes at different scales can be preserved by building a multi-dimensional LBP (MD-LBP) histogram [17]. To do so, LBP codes are calculated at different scales while the combination of the codes identifies the histogram bin that is incremented.

A similar approach can be devised to obtain multi-dimensional LBPV (MD-LBPV) texture descriptors, which incorporate image variance information as adaptive weights to build multi-dimensional LBP histograms [18].

MD-LBPV histograms are calculated as

\[ \text{MD-LBPV}_{P,R} = \{r_1, r_2, \ldots, r_n\}(k_1, k_2, \ldots, k_R) = \sum_{i=1}^{N} \sum_{j=1}^{M} \omega(LBP_{P,R} = \{r_1, r_2, \ldots, r_R\}(i, j), k_1, k_2, \ldots, k_R), \]

with

\[ \omega(LBP_{P,R} = \{r_1, r_2, \ldots, r_R\}(i, j), k_1, k_2, \ldots, k_R) = \begin{cases} f(V) & \text{if } LBP_{P,R} = r_s(i, j) = k_s \quad \forall s \in \{1, 2, \ldots, R\} \\ 0 & \text{otherwise} \end{cases}, \]

and

\[ V = \{\text{VAR}_{P,r_1}(i, j), \text{VAR}_{P,r_2}(i, j), \ldots, \text{VAR}_{P,r_R}(i, j)\}. \]

MD-LBPV based on 2 radii will hence yield a 2-dimensional histogram, MD-LBPV based on 3 radii a 3-dimensional one and so on.

While in MD-LBP the histogram is always incremented in unit values and local contrast information is not utilised, in MD-LBPV local contrast is integrated into the way multi-dimensional texture histograms are generated. Of the various ways of how variance information can be incorporated into MD-LBPV histograms [18], we chose the maximum variance method which uses the maximum value of variance over all scales

\[ f(V) = \max\{\text{VAR}_{P,r_1}(i, j), \text{VAR}_{P,r_2}(i, j), \ldots, \text{VAR}_{P,r_R}(i, j)\}. \]

4. MD-LBPV-based NC Image Analysis

Since NC images are rather challenging due to image noise, dust on lenses, micro-motion of fingers and air bubbles in the immersion oil, we first pre-process the images using a bilateral enhancer filter [19], which we have previously shown to be suitable for NC image enhancement [20].

After the image is enhanced, MD-LBPV features are extracted from the image. For decision making, first each finger is classified, followed by aggregating the outcomes for a patient.

For finger classification, we employ a standard support vector machine (SVM) classifier [21]. Since, we have more than two classes (control, early, active, and late), we employ a one-against-one multi-class SVM [22], where for each SVM, we use a linear kernel, and optimise the cost parameter \( C \in [-1.1; 3.1] \) using a cross validation approach [23].

The final result is then obtained by a voting mechanism where we select the majority class of the finger classifications. Should none of the classes have the majority (i.e. there is a tie between classes) then we reject the diagnosis rather than randomly assigning it to one of the classes. A rejected case should hence be manually inspected.

5. Experimental Results

Experiments were carried out on a dataset of 12 subjects with NC images captured for three to four fingers for each patient and three patients for each class (i.e. control, early, active, and late). The images were obtained at the Dermatology Unit, Clinical Hospital of Chieti, following their standard protocol. A ground truth for all patients was also obtained by manual inspection approved by a consultant. For evaluation, a standard leave-one-out cross validation on a patient basis is performed. That is, the classifier is trained on all but one subject for which the test is run, and the procedure is repeated for all patients (i.e. 12 times in total).

The results are given in Table 1, both in terms of finger and patient classification. From there we can see that our proposed approach does indeed afford very good performance. The finger classification accuracy is 73.17% while for 10 out of 12 patients the correct SD pattern has been identified giving a patient classification accuracy of 83.33%.

For comparison, we give, in Table 2 the results using multi-scale LBPV, that is essentially the method from [12]. It is apparent that here more misclassifications occur, both for finger and patient classification. Overall, only for 8 patients a correct classification is obtained.

6. Conclusions

In this paper, we have presented a holistic method for automatic identification of scleroderma patterns in nailfold capillaroscopy images. Rather than identifying individual capillaries, we perform texture analysis coupled with a
classification approach. In particular, we extract, following an image enhancement step, multi-dimensional LBP variance (MD-LBPV) features from capillary regions to capture multi-resolution texture information. Experimental results confirm the efficacy of our method and improved classification accuracy compared to an earlier approach.

References


