A user dependent multi-resolution approach for biometric data

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Abstract: This paper focuses on the use of a user dependent multi-resolution approach based on local ternary pattern (LTP) in biometric verification. Following an extensive review of the literature on texture descriptors, several methods are compared on well known biometric problems: palm verification and knuckle verification. We propose approaches for extracting a set of local ternary pattern bins separately from the training set of each user, then the Chi square distance is used to compare two templates. The paper is more experimental than novelty in algorithm, our aim is to compare our system with the standard multi-resolution approach, with the novel hierarchical local binary patterns (HLBP) and with different fusions. Extensive experiments conducted over the two well-known biometric characteristics (palmprint and knuckleprint) show the strength of our approach. When each user is given the related selected bins, a near 0 equal error rate is obtained. When the impostor steals the 'selected bins' of the user that he claims to be, our approach slightly outperforms both the standard multi-resolution approach and HLBP. A further improvement in the performance is obtained combining LTP and HLBP.

Keywords: texture descriptors; multi-resolution approach; local binary patterns; LBPs; local ternary pattern; LTP; palmprint verification; knuckleprint verification.

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1 Introduction

The biometric recognition problem has increasingly become one of the most widely studied pattern recognition problems in the 21st century. At stake is the securing of sensitive computer data and systems, cellular telephones, and the personal identities of millions of individuals. Gone are the days of securing sensitive data-based solely on something only a user knows. Passwords, personal identification numbers (PINs), and answers to personal questions are difficult for users to remember, expensive to change, and easy to compromise. Adding a layer of security based on biometrics, such as palm and finger prints, has increasingly become a viable solution to the growing need for tighter security.

Biometrics is the science of measuring and extracting biological features that are common to all people, yet unique to the individual, such as facial structure, fingerprints, and palm prints. Biometric recognition is complicated by a number of associated problems that go beyond identifying the unique biological markers associated with individual identities in a database. Biometric recognition must also be concerned with quality checking, aliveness detection, and multi-modal authentication. Of course, the heart of any biometric recognition systems is the extract of a set of features in the biometric image or pattern that offers the greatest amount of information. In pattern recognition, many new methods have been developed over the last decade for extracting features from an image and for classifying them. Particularly popular in many biometric image classification, verification, and identification systems are texture-based methods, such as those based on local binary patterns (LBPs) (Ojala et al., 2002; Nanni and Lumini, 2008; Fröba and Ernst, 2004; Tan and Triggs, 2007; Liao and Chung, 2007) and Gabor filters (Ong et al., 2008).

Despite the diversity and sheer amount of biometric data available to researchers today, most texture-based methods are tested using one or two datasets that are based on the same biometric trait. Rarely are methods studied that function well across multiple datasets and across multiple biometrics. An examination of the literature shows that different methods perform optimally on different datasets. The aim of this work is to find a generalised method based on LBP/LTP that works well across a number of biometric problems. We accomplish this goal by examining several LBP/LTP approaches for representing images, and we propose a reliable method based on an ensemble where different feature descriptors are combined into an optimal general system. Moreover, we propose extracting different sets of local ternary pattern (LTP) bins separately from the training set of each user.

Extensive experiments conducted over two well-known biometric characteristics show that when each user utilises the related selected bins a near zero equal error rate (EER) is obtained using our system while if the impostor steals the 'selected bins' of the user that he claims to be our approach slightly outperforms both the standard multi-resolution approach and HLBP.

The remainder of this paper is organised as follows. In Section 2 we discuss research in texture-based methods for biometric verification that use the biometric traits examined in this study. In Section 3 we introduce the feature extraction methods and the classification system investigated in this work. In Section 4 we describe the datasets and the testing protocols used to test our system. In Section 5 we report experimental results obtained on different biometric traits. Finally, in Section 6 we draw conclusions and discuss directions for future research.

2 Related work

In this section we review techniques for classifying the biometrics explored in this study: palm verification and knuckle verification.

2.1 Palm verification

Palm verification is based on the acquisition of hand images using a digital camera. Characteristics in a palmprint impression are then used to verify a person's identity. Features extraction methods that have a proven track record in palm verification can be divided into the following three categories (Kumar and Zhang, 2005):

1 texture-based approaches, e.g., Gabor filters (Zhang et al., 2003; Kong et al., 2003), discrete cosine coefficients (Kumar and Zhang, 2004a, 2004b), and wavelets (Zhang and Zhang, 2004)

2 line-based approaches, e.g., line matching (Zhang and Shu, 1999) and line detection (Kumar et al., 2003)

3 Appearance-based approaches, e.g., Fisherpalm (Lu et al., 2003a, 2003b), eigenpalm (Lu et al., 2003a, 2003b), and 2DPCA (Zuo et al., 2006).

Performance of a palm verification system is hampered by using only a single descriptor. Ideally a palmprint verification system should be based on the fusion of several descriptors (Kumar and Zhang, 2005, 2004b; Kong et al., 2006; Nanni and Lumini, 2009a, 2009b). In Kumar and Zhang (2005), for example, the authors show how combining Gabor filters, line detectors, and principal component analysis (PCA), significantly increases classification performance. An ensemble of classifiers is built from a Palm image in Nanni and Lumini (2009a, 2009b) by extracting five subimages. Feature vectors are then extracted from these subimages, one for each of the three feature extraction methods investigated in that study. The final score is obtained by combining the scores of the different palmprint representations.

2.2 Knuckle verification

Gaining in popularity is the use of the entire finger biometric, see e.g., Li et al. (2004) and Ribaric and Fratric (2005). So far only the inner and outer knuckle prints have been investigated. In Li et al. (2004), the lines in the inner skin of the knuckle of the finger were found to be a viable biometric marker. Several studies have used these markers. In Ribaric and Fratric (2005), for example, an image-based finger matcher is proposed where the finger image is projected onto a lower-dimensional space using PCA, in Zhao et al. (2009), a new method for line feature knuckleprint matching is proposed, and in Nanni and Lumini (2009b), a subset of Gabor filters is selected from the entire image. In Zhang et al. (2010) the outer finger-knuckle-print, or the patterns formed by the outer surface around the phalangeal joint of the finger, was examined. In that study a novel Gabor-based feature extractor was employed.

3 Proposed approach

As noted above, biometric verification is a difficult machine classification problem that is best handled by combining multiple descriptors to boost performance. Good descriptors are invariant to image rotation and scale. In addition, they are robust in terms of variations in illumination.

In our investigation, the same classification approach is used in all the datasets. It is based on the following steps: enhancement, tessellation by a square non-overlapping grid and feature extraction, matching with a set of distances (one for each selected feature vector) that are combined by sum rule.

The pre-processing is performed as in Connie et al. (2005), with the normalised image computed using the following operation:

$$I'(x,y)=\begin{cases} m_n + B \ if \ I(x,y) > m \\ m_n - B \ otherwise \end{cases} \quad B=\sqrt{\frac{n_n(I(x,y)-m)^2}{n}},$$

where m and n are the mean and variance of the image, respectively, and m_n and n_n are set to 100.

Before the feature extraction step, each image is first decomposed into non-overlapping square cells of fixed dimension *dim1* × *dim2*. The following values are used in this study: *dim*1 = 16 and *dim*2 = 32.

The matching value between two images is calculated by a distance function. In this study, we use the chi square distance. Finally, these distances (one for each square cell) are combined by sum rule.

Our idea is to extract a set of user dependent bins from LTP. We test two approaches for extracting the user-dependent bins:

1 VAR, which involves selecting 75% of the histogram bins with the highest variance from among the bins selected using DOM. DOM chooses a set with a cardinality whose minimum is between 250 and 75% of the totals number of bins that contain the highest occurrences (notice that when all the rotation invariant bins are used we have more than 1,000 bins, so we are selecting only a small subset).

2 SFFS, which involves selecting 75% of the histogram bins that minimise the intra-class distance among the training images. The selection is performed by sequential floating forward selection (SFFS), among the bins selected with VAR.

The best approach, validated in Section 5 is the fusion between LPT and HLBP. The remainder of this section describes several texture descriptors examined in our proposed ensemble methods.

3.1 Invariant LBPs

LBP (Ojala et al., 2002) is a histogram based on a statistical operator that is calculated by examining the distribution of grey scale values of a circularly symmetric neighbour set of P pixels around the value of a central pixel q_c on a circle of radius R. Formally, the LBP operator is defined as follows:

$$LBP(P,R) = \sum_{p=0}^{P-1} s\left(q_p - q_c\right)2^p$$

where P is the number of pixels in the neighbourhood, R is the radius, and $s(x) = 1$ if $x \geq 0$, otherwise 0. The histogram of these binary numbers is then used to describe the texture of the image. Two types of patterns are distinguished: uniform patterns, which have at most two transitions from 0 to 1, and non-uniform patterns.

We use a multi-resolution descriptor in this study that is obtained by concatenating histograms calculated with the following parameters: ($P = 8$; $R = 1$) and ($P = 16$; $R = 2$).

In Ahonen et al. (2009) a rotation invariant image descriptor is proposed that is based on uniform LPB that is called the local binary pattern histogram Fourier (LBP-HF). LBP-HF features are extracted using the discrete Fourier transform. It extracts a class of features that are invariant to the rotation of the input image starting from the histogram rows of the uniform patterns.

In Guo et al. (2010), the hierarchical multi-scale LBP is presented. It is an approach that improves performance by extracting information from the non-uniform bins. The hierarchical multi-scale LBP is based on a multi-resolution approach that utilises three different radii:

1 the LBPs for biggest radius are extracted first, then

2 for the 'non-uniform' patterns, the counterpart LBPs of smaller radius is extracted, finally

3 among the new LBPs, the 'non-uniform' patterns and 'uniform' patterns are extracted using an even smaller radius.

This procedure is iterated until the smallest radius is used to extract features.

Until recently, LBP descriptors have utilised only the uniform patterns. Recent work has attempted to augment LBP by using non-uniform patterns. In Zhou et al. (2008) uniform patterns are combined with a few non-uniform patterns to improve performance. In Liao et al. (2009), rotation invariant patterns are selected, instead of the uniform patterns. The researchers in that study propose choosing patterns that represents 80% of the patterns in the training data. Several other variants have recently been proposed, see e.g., (Nanni et al., 2010).

3.2 Local ternary patterns

The LTP (Tan and Triggs, 2007) is a generalisation of LBP. LTP represents the grey-scale differences between pixels using a ternary rather than a binary value as in LBP. The difference between the grey value of a pixel x from the grey values in one of its neighbourhood u assumes the three values by applying a threshold τ (so LTP descriptors should be less sensitive to noise):

$$d = \begin{cases} 1 & u \geq x + \tau \\ 0 & x - \tau \leq u < x + \tau \\ -1 & otherwise \end{cases}$$

The ternary pattern is split into two binary patterns by considering the positive and negative components according to the following binary function $b_c(x)$, $c \in \{-1, 1\}$

$$b_c(x) = \begin{cases} 1 & x = c \\ 0 & otherwise \end{cases}$$

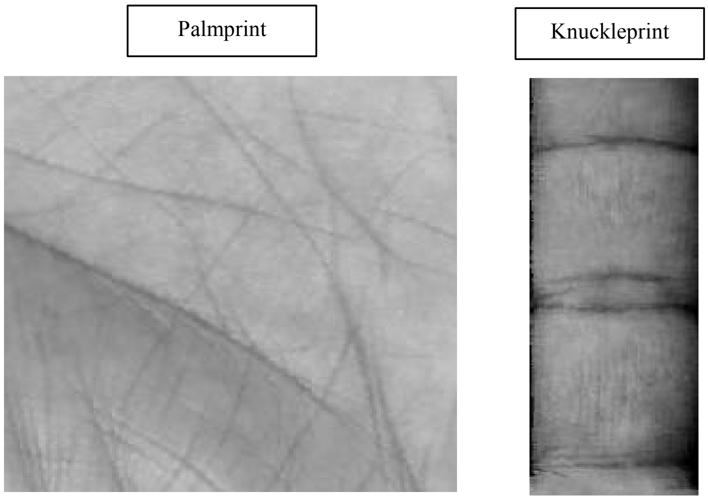
The histograms computed from these two patterns are then concatenated. The feature vector is the concatenation of these two histograms. In this study we use (P = 8; R = 1) and (P = 16; R = 2) and two implementations of LTP: a LTP variant where the uniform bins are considered (*LTPu*) and a variant where the rotation invariant bins are considered (*LTPri*). For more details on uniform bins and rotation invariant bins, see (Ojala et al., 2002).

4 Datasets and protocols

We test our method on the palm and knuckle benchmark datasets. A sample image from each dataset is shown in Figure 1. For the palm prints, we use the inkless hand images obtained from a digital Camera. The database contains seven samples from each user, for 100 users. For the knuckle verification problem, we report results obtained using only the middle-finger which are extracted as in Nanni and Lumini (2009b). The palm images are extracted as in Nanni and Lumini (2009a, 2009b).

Performance is measured by means of the well known EER. The EER is a unique measure for characterising the security level of a biometric system. It is the error rate when the frequency of fraudulent accesses (false match rate, FMR) and the frequency of rejections of people who should be correctly verified (false non-match rate, FNMR) assume the same value.

Figure 1 Samples from the datasets



5 Experimental results

In Table 1, we compare the performance of the following methods by considering three images (the first session) belonging to the training set and the other four images making up the testing set:

- LBP/LTP-u(P, R), LBP/LTP, with radius R and P neighbourhood, where all the uniform bins are used
- LBP/LTP-ri(P, R), LBP/LTP, with radius R and P neighbourhood, where all the rotation invariant bins are used
- LBP/LTP-riu2(P, R), LBP/LTP, with radius R and P neighbourhood, where all the rotation invariant uniform bins are used
- HLBP, the hierarchical LBP using the original code shared by the authors of HLBP
- LTP-x(P, R)-VAR, LTP, with radius R and P neighbourhood where the x bins are used, coupled with our approach named VAR
- LTP-x(P, R)-SFFS, LTP, with radius R and P neighbourhood where the x bins are used, coupled with our approach named SFFS
- FUS1, the fusion by sum rule between LTP-u(8, 1)-VAR, and LTP-u(16, 2)
- FUS2, the fusion by sum rule between LTP-u(8, 1)-VAR, HLBP, and LTP-u(16, 2)

Before each fusion the distances are normalised to mean 0 and standard deviation 1.

For each cell in Table 1, two values *X*(*Y*) are reported where:

- *X*, is the EER obtained when each user uses its own 'selected bins'
- *Y*, is the EER obtained when the impostor steals the 'selected bins' of the user that he claims to be.

Table 1 Performance comparison

Method		*Palm*	*Knuckle*
LBP-u(8, 1)		5.1	4.0
LBP-ri(8, 1)		10.8	12.3
LBP-riu(8, 1)		9.8	11.8
LBP-u(16, 2)		5.2	4.0
LBP-ri(16, 2)		29.1	20.3
LBP-riu(16, 2)		9.1	7.3
LTP-u(8, 1)		4.7	3.7
LTP-ri(8, 1)		6.9	6.8
LTP-riu(8, 1)		8.7	6.9
LTP-u(16, 2)		4.7	4.1
LTP-ri(16, 2)		30.8	18.4
LTP-riu(16, 2)		8.0	6.6
LTP-u(8, 1) + LTP-u(16, 2)		4.2	3.4
HLBP		5.0	3.6
LTP-u(8, 1)	VAR	0.25 (5.3)	0 (3.7)
	SFFS	0.25 (5.4)	0 (4.4)
LTP-ri(8, 1)	VAR	0.25 (9.6)	0 (14.3)
	SFFS	0.25 (9.6)	0.3 (15.5)
LTP-u(16, 2)	VAR	1.83 (7.4)	0.25 (8.8)
	SFFS	3.5 (7.7)	0 (11.2)
FUS1		0.5 (4.2)	0.25 (3.2)
FUS2		1.5 (*4.0*)	0.25 (*3.0*)

A number of experimental findings can be extracted from the results reported in Table 1:

- using a simple distance measure LTP does not outperforms LBP, as when a high performing classifier is used [see the comparison between LBP and LTP reported in Nanni et al. (2010)]
- the multi-resolution method based on LTP outperforms HLBP
- the best LTP/LBP setting is to use all the uniform bins
- our approach obtains a near 0 EER when each user uses its own selected bins
- FUS1 performance, when the select bins are stolen, is equal or slightly better than the standard multi-resolution approach
- combining different approaches maximises performance. FUS2, based on the fusion of a multi-resolution LTP and on HLBP, obtains the best EER in both the datasets. Notice that, as shown in Guo et al. (2010) HLBP obtains a very high performance compared with subspace approaches.

The main drawback of the propose approach is that it needs a training set for each user, while both LTP and HLBP are training free approaches.

6 Conclusions and discussion

This paper focused on the study of texture descriptors in biometric verification. Based on an analysis of prior research, we propose a multi-resolution approach based on LTP that works well in two different problems: palm verification; and knuckle verification. Our aims are:

- to compare standard multi-resolution approach with the novel hierarchical local binary patterns (HLBP)
- to study the fusion between LTP and HLBP
- to report the performance obtained with a user dependent bin selector.

When the user dependent bins selection is performed and each matching is performed so that each user uses its set of selected bins, we obtain a near 0 equal error rate. When the impostor steals the 'selected bins' of the user that he claims to be our approach slightly outperforms both the standard multi-resolution approach and HLBP.

Another interesting finding is that LTP does not drastically outperform LBP, as shown in other works (see, e.g., Nanni et al., 2010). In our opinion this is due to that in this work we use a simple distance measure while in Nanni et al. (2010) an advanced machine learning approach, the support vector machine (SVM), was used. SVM probably exploits the information extracted using LTP.

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References

Ahonen, T., Matas, J., He, C. and Pietikäinen, M. (2009) 'Rotation invariant image description with local binary pattern histogram Fourier features', *Image Analysis, SCIA 2009 Proceedings, Lecture Notes in Computer Science*, Vol. 5575, pp.61–70.

Connie, T., Jin, A.T.B., Ong, M.G.K. and Ling, D.N.C. (2005) 'An automated palmprint recognition system', *Image and Vision Computing*, Vol. 23, pp.501–515.

Fröba, B. and Ernst, A. (2004) 'Face detection with the modified census transform', *Proc. 6th Int. Conf. on Face and Gesture Recognition – FG 2004*, May, Vol. 91–96, Seoul, Korea.

Guo, Z., Zhang, L., Zhang, D. and Mou, X.Q. (2010) *Hierarchical Multiscale LBP for Face and Palmprint Recognition*, ICIP.

Kong, A., Zhang, D. and Kamel, M. (2006) 'Palmprint identification using feature-level fusion', *Pattern Recognition*, Vol. 39, pp.478–487.

Kong, W.K., Zhang, D. and Li, W. (2003) 'Palmprint feature extraction using 2-D Gabor filters', *Patt. Recog.*, Vol. 36, pp.2339–2317.

Kumar, A. and Zhang, D. (2004a) 'Integrating shape and texture for hand verification', *Proceedings of the International Conference on Image & Graphics, ICIG 2004*, pp.222–225, Hong Kong.

Kumar, A. and Zhang, D. (2004b) 'Palmprint authentication using multiple classifiers', *SPIE Symposium on Defense & Security – Biometric Technology for Human Identification*, 12–16 April, Vol. 5404, pp.20–29, Orlando, Florida, USA.

Kumar, A. and Zhang, D. (2005) 'Personal authentication using multiple palmprint representation', *Pattern Recognition*, Vol. 38, pp.1695–1704.

Kumar, A., Wong, D.C.M., Shen, H. and Jain, A.K. (2003) 'Personal verification using palmprint and hand geometry biometric', *AVBPA*, pp.668–675, Guildford, UK.

Li, Q., Qiu, Z., Sun, D. and Wu, J. (2004) 'Personal identification using knuckleprint', *SINOBIOMETRICS*, pp.680–689.

Liao, S. and Chung, A.C.S. (2007) 'Face recognition by using elongated local binary patterns with average maximum distance gradient magnitude', *Computer Vision – ACCV*, pp.672–679.

Liao, S., Law, M.W.K. and Chung, A.C.S. (2009) 'Dominant local binary patterns for texture classification', *IEEE Transactions on Image Processing*, Vol. 18, No. 5, pp.1107–1118.

Lu, X., Zhang, D. and Wang, K. (2003a) 'Fisherpalms based palmprint recognition', *Patt. Recog. Lett.*, Vol. 24, pp.2829–2838.

Lu, G., Zhang, D. and Wang, K. (2003b) 'Palmprint recognition using eigenpalm-like features', *Patt. Recog. Lett.*, Vol. 24, pp.1473–1477.

Nanni, L. and Lumini, A. (2008) 'Local binary patterns for a hybrid fingerprint matcher', *Pattern Recognition*, Vol. 41, No. 11.

Nanni, L. and Lumini, A. (2009a) 'Ensemble of multiple palmprint representation', *Expert Systems with Applications*, Vol. 36, No. 3, pp.4485–4490.

Nanni, L. and Lumini, A. (2009b) 'On selecting Gabor features for biometric authentication', *International Journal of Computer Applications in Technology*, Vol. 35, No. 1, pp.23–28.

Nanni, L., Brahnam, S. and Lumini, A. (2010) 'A study for selecting the best performing rotation invariant patterns in local binary/ternary patterns', *Proceedings of the International Conference on Image Processing, Computer Vision, and Pattern Recognition (IPCV'10)*.

Ojala, T., Pietikainen, M. and Maeenpaa, T. (2002) 'Multiresolution gray-scale and rotation invariant texture classification with local binary patterns', *IEEE TPAMI*, Vol. 24, No. 7, pp.971–987.

Ong, M.G.K., Connie, T. and Teoh, A.B.J. (2008) 'Touch-less palm print biometrics: novel design and implementation', *Image and Vision Computing*, Vol. 26, No. 12, pp.1551–1560.

Ribaric, S. and Fratric, I. (2005) 'A biometric identification system based on eigenpalm and eigenfinger features', *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 27, No. 11, pp.1698–1709.

Tan, X. and Triggs, B. (2007) 'Enhanced local texture feature sets for face recognition under difficult lighting conditions', *Analysis and Modelling of Faces and Gestures*, Vol. 4778, pp.168–182, LNCS.

Zhang, D. and Shu, W. (1999) 'Two novel characteristics in Palmprint verification: datum point invariance and line feature matching', *Patt. Recog.*, Vol. 32, No. 4, pp.691–702.

Zhang, D., Kong, W.K., You, J. and Wong, M. (2003) 'Online palmprint identification', *IEEE Trans. Patt. Anal. Mach. Intell.*, Vol. 25, pp.1041–1050.

Zhang, L. and Zhang, D. (2004) 'Characterization of palmprints by wavelet signatures via directional context modeling', *IEEE Trans. Sys. Man Cybern. Part B*, pp.1335–1347.

Zhang, L., Zhang, L., Zhang, D. and Zhu, H. (2010) 'Online finger-knuckle-print verification for personal authentication', *Pattern Recognition*, Vol. 43, No. 7, pp.2560–2571.

Zhao, R., Li, K., Liu, M. and Sun, X. (2009) 'A novel approach of personal identification based on single knuckleprint image', *Asia-Pacific Conference on Information Processing*, Vol. 2, pp.218–221.

Zhou, H., Wang, R. and Wang, C. (2008) 'A novel extended local binary pattern operator for texture analysis', *Information Sciences*, Vol. 178, No. 22, pp.4314–4325.

Zuo, W., Zhang, D. and Wang, K. (2006) 'An assembled matrix distance metric for 2DPCA-based image recognition', *Pattern Recognition Letters*, Vol. 27, pp.210–216.