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Reducing dense local feature key-points for faster iris recognition☆

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ABSTRACT

Iris recognition has gained much attention in research and commercialization during the last decade. For a large population, the matching time of iris biometric system is much slower than the requirement. More the enrolled population size, higher the identification delay. To combat the delay without compromising accuracy of the system, the proposed method introduces a density-based spatial clustering and key point reduction to be applied on Phase Intensive Local Pattern (PILP) based dense feature extracted from the image. The reduction technique can also work with other dense local features. The reduction method is investigated whether it harms the accuracy of iris biometric system with respect to PILP. Widely used databases: BATH and CASIAv3 are used for experimentation. The technique is found successful in reducing representative key-points, thereby speeding up the match time up to five times. This improvement in 1:1 match-time is significant, and becomes more meaningful in identification for a large population.

1. Introduction

Feature extraction is an important task in various applications of computer vision like object recognition [1], visual tracking, shape modeling, security through biometrics [2,3] etc. Finding appropriate discriminative feature for a specific application is quite crucial and challenging. It can be global or local depending on the nature of extraction. Since the last few decades, local feature has been extensively used in real-world applications like object recognition [4–6] and image retrieval [7–9]. They are popular because of their computational efficiency, resistant to partial occlusion, and invariance to geometric transformations. Local features also find its application in iris and ocular biometrics, which are proven to be robust than face biometrics [10]. One such recently developed feature specifically designed for recognition of ocular recognition (whose construction is inspired by Phase Intensive Global Pattern (PIGP) [11]) is called Phase Intensive Local Pattern (PILP). It is capable of extracting high dimensional subtle local features existing in ocular region [12]. PILP is a multi-scale local feature extraction technique capable of reducing dense key-points that includes, both gross and fine

Abbreviations: DBSCAN, Density-Based Spatial Clustering of Applications with Noise; LDA, Linear Discriminant Analysis; NIR, Near infrared; PCA, Principal Component Analysis; PILP, Phase Intensive Local Pattern; ROC, Receiver Operating Curve; SIFT, Scale Invariant Feature Transform; SURF, Speeded Up Robust Features.

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Table 1
State-of-the-art feature reduction methodologies for local feature descriptors.

Year	Author	Approach	Method	Remark
2004	Ke and Sukthankar [13]	Dimensionality reduction	Projecting to lower dimensional space using PCA	More distinctive
2007	Hua et al. [14]	Dimensionality reduction	Projecting to lower dimensional space using LDA	Better than PCA
2012	Alitappeh et al. [15]	Key-point reduction	Subtractive clustering	Tries to remove similar key-points
2013	Yuasa and Wada [17]	Key-point reduction	Importance measure using Diverse Density	Measures robustness and distinctiveness

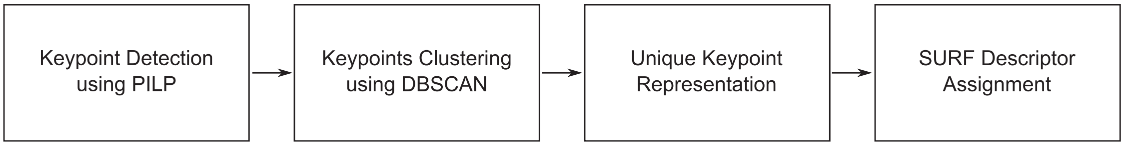

Fig. 1. Block diagram for key-point reduction of a dense feature: PILP.

features in and around the eye region. It detects a sufficiently large number of densely positioned key-points, which give an excellent recognition accuracy, but at the same time, it is computationally very expensive. The large number of detected key-points is the main cause of its slowness. The proposed method attempts to reduce the number of key-points efficiently by grouping few very closely placed key-points together into a single key-point to achieve a trade off between time and accuracy, without sacrificing significantly in the performance.

The rest of the article is organized as follows: Section 2 briefs the state-of-the-art of the different approaches to iris key-point reduction schemes deducing the problem statement, Section 3 describes the process of reducing the dense feature, Section 4 puts forward experimental findings in favor of using the reduction technique and analyses how accuracy is retained even after key-point reduction. Finally, Section 5 highlights the benefits of the reduction method and discussed its possible usage scope.

2. Related work

One of the early study in the direction of reduction of local feature is PCA-SIFT by Ke and Sukthankar, who proposed the dimensionality reduction for Scale-Invariant Feature Transform (SIFT) [13]. It performs projection of the high dimensional feature vector of SIFT onto a lower dimension using Principal Component Analysis (PCA). It reduces the size of the descriptor and was also able to reduce the presence of high frequency noise in it. Hua later observed PCA-SIFT to be less discriminative, and suggested a similar reduction technique using Fisher analysis : Linear Discriminant Analysis (LDA) [14], which better projection that well separate data in the feature sub-space.

In a different paradigm of approach to the priors, Alitappeh et al. has reduced SIFT descriptor by applying subtractive clustering [15]. They decreased the size of features by removing redundant key-points bearing high degrees of similarity with others. The remaining key-points are naturally more distinctive than the pruned ones, and hence found to be better candidate for recognition. In another work by Rudinac *et al.*, the number of key-points of local features is reduced in two stages [16]. In first stage; they rejected points close in a specified neighborhood using a spatial criterion followed by selecting strong key-points with high entropy. Yuasa and Wada proposed a measure for robustness and distinctiveness of the local feature based on diverse density [17]. Based on this measure, they identified key-points as strong or weak. Stronger key-points lead to better matching. Table 1 outlines various approaches schemed by researchers towards feature reduction of local features. The survey clearly highlights that no neighborhood based clustering has been applied to dense iris key-points, which we propose in this paper.

3. Key-point reduction of dense feature

The overall feature reduction and extraction scheme is depicted in Fig. 1. Essentially the reduction methodology is a part of post-processing after all dense key-points are discovered. Each steps are discussed in details in the following subsections.

3.1. Key-points detection

Key-point detection through Phase Intensive Local Patterns (PILP) is obtained with a variable size filter depending on different scales. These scales are varied from 3 to 9 at a step of 2. Correspondingly the filter sizes also increases from 3×3 to 9×9. At a given scale Δ, the PILP at a pixel (xc, yc) with respect to its $\Delta^2 - 1$ neighbors considering a phase-tilt ϕ can be derived convolving the filter. For each scale, the value of ϕ is varied from 0 to $\frac{7\pi}{4}$ with an leap of $\frac{\pi}{4}$, resulting eight filters as shown in Fig. 2. It is found that only four out of these filters are unique, as shown in Fig. 3. Finally for each pixel location in the convolved image for each scale, local extrema are identified as potential key-points. Now selecting a suitable threshold value, high enough to eliminate the edge features. Fig. 4 illustrates the whole PILP key-point detection method