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A new entropy function and a classifier for thermal face recognition

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ABSTRACT

An attempt is made to devise a new entropy function that goes beyond the existing entropy functions with its ability to change the information source values (gray levels in an IR image) and its information gain by selecting its parameters. Our objective is to improve the existing results on the Infra-Red thermal face recognition by using this entropy function that possesses peculiar characteristics such as splitting and inverting which impart a discriminating power. To cash on its discriminating power, two types of features Effective Gaussian Information (EGI) source and Effective Exponential Information (EEI) source functions are developed. To classify the features, we have modified our earlier classifier (Mamta and Hanmandlu, 2014) using the new entropy function. The performance of the new features and new classifier is tested on IR face databases under the constrained and the unconstrained conditions with regard to occlusion, noise and low resolution. A comparison of performance shows that the new entropy function outperforms the existing entropy functions such as Shannon, Renyi, Tsallis and Pal and Pal, Collision, Min entropy and Susan–Hanman.

1. Introduction

Face is one of the most challenging biometric modalities and face recognition is the most natural mode of identification. Unlike other modalities like iris, fingerprint, palmprint, and knuckle print, face is a passive biometric whose frontal and profile can be captured from a distance without an active participation of the user. This advantage makes it useful for the security and surveillance tasks.

Significant research has been done on face recognition using visual imagery, which is easily affected by the variations in the illumination conditions (Adini et al., 1997), face expression (Tian et al., 2001), pose variations due to reflective nature of incident light in visual band (Ben-Arie and Nandy, 1998). As a remedy to this problem, the use of thermal infrared band is being investigated for face recognition. Thermal infrared sensor measures the heat energy radiation emitted by the face rather than the light reflectance (Wolff et al., 2003). Hence IR camera offers a great advantage on face recognition under low illumination conditions or darkness (Kong et al., 2007; Zhao et al., 2003).Thermal IR spectrum reveals the anatomical information of a subject useful in detecting the disguised faces (Pavlidis and Symosek, 2000). Face detection (Dowdall et al., 2003) and segmentation are easier to accomplish in the thermal band. Thermal face recognition system performs better than the visual face recognition system under illumination variation (Kong et al., 2005). However there are multiple factors such as low resolution, high level of noise in the images, sensitivity to the temperature variation and opacity to glass; these factors discourage the exploitation of thermal images for face recognition. Attempts are already afoot to improve the performance of the face recognition system by fusing the visual and infrared modalities. A study of IR modality (Socolinsky et al., 2003; Socolinsky and Selinger, 2002) reveals that IR imagery is highly sensitive to the occlusion in a face caused by the eye glasses. One way to mitigate this problem is to go in for the fusion of visual and thermal spectra.

Arandjelovic et al. (2006) have presented a fusion algorithm based on holistic and local features whereas Kong et al. (2007) have developed a data-fusion scheme in which the eye-glass region is replaced with the average of the eye thermal region to improve the recognition accuracy. Singh et al. (2004) have proposed the image-based fusion that operates in the wavelet domain and also the feature level fusion that operates in the Eigen space domain. Fang et al. (2009) demonstrate that the local feature extraction is more appropriate than the holistic feature extraction for the infrared face images whereas Li et al. (2007) demonstrate that Local binary pattern (LBP) is better than Principal component analysis (PCA). Wu et al. (2008) have proposed a skin heat transfer (SHT) model to reduce the effect of temperature variation on the infrared face and Lu et al. (2010) have converted the IR images into

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blood perfusion type and applied the block-wise PCA on the fused images. In this paper we are concerned with the issue of high level occlusion, noise and very low resolution in IR face images.

1.1. Motivation

Face recognition under the constrained conditions has reached a certain level of accomplishment as can be gauged by the two successful biometric systems: Smartgate (Smartgate website) in Australia and border control system in Hong Kong (Chinese/Hong Kong border automated with biometrics, 2007) both of which need the user's cooperation in the constrained environment. A surveillance system called Biometric Optical surveillance System (BOSS) was sponsored by the Homeland security of US for the identification of faces in a crowd. The performance of these systems degrades under the unconstrained conditions that are prevalent in surveillance applications. Spurred by the success of these initial attempts, we have embarked on developing an IR face based recognition system capable of performing in an open environment like that exists in surveillance applications. As the IR face recognition system is susceptible to low resolution, high level noise and occlusion, our aim is to make it robust with the help of a new entropy function.

We note here that the entropy based feature extraction methods are not as popular as the conventional methods like Principal Component Analysis (PCA), Independent Component Analysis (ICA), Linear Discriminate Analysis (LDA), Gabor filter and wavelets, and Local binary Pattern (LBP) to mention a few though the entropy functions have made inroads into image processing applications such as image indexing (Koskela et al., 2004; Wang, et al., 1997), segmentation and formulation of similarity measures (Jain et al., 1995; Moshfeghi et al., 2004). Our endeavor is to tap the potential of the new entropy function for feature extraction and classification in biometrics.

1.2. A brief survey of entropy functions

Entropy is a measure of uncertainty or disorder in a system. Shannon and Weaver (1949) defined the entropy as negative logarithmic function of probability of the occurrences of an event. Several authors (Pun, 1981; Pal, 1982) have used Shannon entropy for image processing and pattern recognition. Tsallis et al. (1998) and Renyi (1970) and Tsallis et al. (1998) have generalized the Shannon entropy by introducing a parameter called the power of probability which controls the shape of the probability distribution. The Renyi entropy is more sensitive to the event that occurs frequently when α takes large positive values. The Tsallis entropy (Tsallis et al., 2001) is non-extensive or non-additive unlike Shannon entropy. Owing to this property, Albuquerque et al. (2004) have applied the principle of maximum Tsallis entropy for image segmentation. The logarithmic gain function of Shannon and Renyi entropies creates problems when either the probability of occurrence of an event is zero or when the events are equally likely and the number of events is very large. Pal and Pal (1992) have replaced the logarithmic gain in the Shannon entropy function (Shannon, 1948) with the exponential gain. Hanmandlu and Das (2011) have extended the Pal and Pal entropy by introducing a polynomial in the exponential gain function and used it for the image retrieval. Recently Mamta and Hanmandlu (2013) have used the entropy function called Hanman–Anirban entropy to generate Local Principal Independent Components (LPIC) features for ear recognition. Susan and Hanmandlu (2013) have derived the nonextensive Gaussian entropy from Hanman–Anirban entropy for the characterization of texture.

This paper proposes a new entropy function inspired from the work of Hanmandlu and Das (2011) with far reaching capabilities to deal with the unconstrained environment posed by the IR face images at the surveillance site.

1.3. Motivation for the new entropy for IR face biometric

The motivation for the new entropy function is stemmed from the observation that the Hanman–Anirban entropy function has no provision to change the shape of the probability distribution though it has free parameters to modify the exponential gain function that accounts for the varying uncertainty. This deficiency is sought to be removed in the new entropy function by providing more teeth in terms of changing not only the parameters of the polynomial in the exponential gain function but also the information source values. Unlike the visual face images, IR images that possess thermal characteristics are difficult to analyze by the human brain. They are easily affected by the temperature variation, occlusion, and noisy environment thus necessitating a flexible biometric system that can handle the inherent uncertainty in the IR images.

The organization of this paper is as follows. Section 2 describes the formulation of new entropy along with its properties. Section 3 introduces new features based on this entropy function. A classifier based on the new entropy function is developed using t-norms in Section 4. The database for the evaluation of the new entropy based biometric system is described in Section 5. Results of IR face based authentication are discussed in Section 6 and the results of IR Veins and ORL database are presented in Section 7. The conclusions are given in Section 8.

2. Entropy formulation

The uncertainty in the information source is represented by different entropy functions. The Shannon entropy as a measure of uncertainty in the probability distribution is given by

$$H^{Sh} = -\sum p \log p \tag{1}$$

where $\log p$ is the logarithmic gain function and $\sum p = 1$. Renyi (1970) and Tsallis et al. (1998) have generalized the Shannon entropy by incorporating a parameter α. The Renyi entropy is defined as

$$H^{RN} = \frac{\log \sum p^{\alpha}}{1-\alpha} \tag{2}$$

The Tsallis entropy (Tsallis et al., 2001) that satisfies the non-extensive property is defined as

$$H^{TS} = \frac{1-\sum p^{\alpha}}{\alpha - 1} \tag{3}$$

Pal and Pal (1992) touch upon the exponential gain function as a remedy to the shortcomings of the logarithmic gain function of Shannon by coming up with the entropy function as

$$H^{PP} = \sum p e^{1-p} \tag{4}$$

The above entropy functions that have no free parameters in the gain functions only give the uncertainty in the probability distribution.

The frequency of occurrences of gray levels in an image depicted by a histogram gives the probability distribution whereas the membership function fitted to the gray levels gives the gray level distribution. The entropies associated with the probabilities do not serve the purpose of describing the uncertainty associated with the gray level distribution in an image called the qualitative information or possibility. To address this issue, Hanmandlu and Anirban Das have devised the information theoretic entropy function christened as Hanman–Anirban entropy function. This has the provision to represent the uncertainty in both the probabilistic and possibilistic domains unlike the conventional