GABOR WAVELETS FOR HUMAN BIOMETRICS

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Gabor Wavelets for Human Biometrics 蓋博小波在人體識別中的應用

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Abstract

Wavelets are frequently used in biometric and other image processing based applications. Among different wavelets, Gabor wavelet is of high interest among the researchers. Due to the appropriateness and suitability of Gabor wavelet to explain image decomposition in mammalian vision from both spatial and frequency domain is well established. Gabor wavelet can be used in facial image processing for face and facial expression recognition and analysis. At the earlier part of this thesis we determine the discrimination characteristics of different filters of Gabor wavelet by the means of a face recognition system. At this stage we also study the recognition performance of different summation based Gabor feature representations. Later a facial expression intensity measurement system is implemented using Gabor wavelet and self organizing maps (SOM) which is able to measure intensity of an emotion from a facial expression image in the form of fuzzy-membership values of three intensity classes- less, medium and high. In another application to recognize American Sign Language (ASL) alphabets Gabor wavelet is used as initial feature extractor for hand signed alphabets recognition. Finally at the end of this thesis we propose a method to extract blood vessels from retinal fundus images which can then be used as biometric measure for human identification and authentication. We show that using phase congruency which is acquired applying Log-Gabor wavelet on images can be used to segment retinal blood vessels for human identification. As a whole this thesis studies different aspects of Gabor wavelet referred to different computer vision based human biometric applications.

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