使用紅外線熱電感測器實現人員即時辨識之生物檢測系統

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摘要

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在本研究中我們提出新穎的光學運算感測系統,在系統中引入生物測定觀念以及非 成像式之光學特徵擷取技術來捕捉步行者之動態熱像特徵,加上智慧型特徵分類訓練法 則,成功地實現了人員即時辨識。

生物體特徵的選取是生物檢測/辨識系統中最關鍵的一環。從熱源的觀點來看,人 體是一個非常好的紅外線輻射源,在常溫環境中人體會持續地散發出紅外輻射。而熱源 的分佈強度取決於體型的高矮胖瘦及皮膚上各處的紅外輻射發射率。當人在行走時,因 為身體各個部位的擺動方式不同,產生了不同風格的動態行走特徵,因此,結合了身材 特徵以及個人的行走風格,即使走在同一路線上,所散發出的紅外熱源分佈對於周圍的 感測器也會產生獨特的訊號。

在生物特徵撷取方面,我們使用紅外線熱電感測器,此元件在室溫下對於偵測紅外 輻射訊號有很好的工作效能,且有低功率損耗、低成本的優點,因此被廣泛的應用在各 種不同的系統中。當感測器感應到溫度變化時,感測器內晶體的熱電特性,將會產成電 荷充電效應,進而轉換產生電壓訊號。我們利用感測器去偵測人員走動所產生的熱輻 射,系統中以吾人發明的特殊菲涅耳透鏡陣列,結合光學運算及感測技術,達到無需成 像直接捕捉步行者之熱像生物特徵的效能。

在特徵分類辨識方面,本論文發展出兩套分別以類比式生物特徵以及數位式生物特 徵為基礎的生物檢測/辨識系統。我們成功的展示藉由適當的感測模組結構,加上特徵 擷取方法以及特徵訓練演算法,這些生物檢測系統可以達成固定行走路線及自由路線的 即時人員辨識並有非常好的辨識效果。

Ι

Pyroelectric Infrared Biometric Systems for Real-Time Human Identification

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ABSTRACT

In this study, we proposed novel designs for computational systems that use biometrics and non-conventional imaging approaches to capture thermal motion features of humans to achieve real-time path-dependent and path-independent gait for human identification.

Feature representation is key to biometric recognition system. From a thermal perspective, each person represents a distributed infrared source, the distribution function of which is determined by shape and IR emissivity of the skin at every point. When humans walk, the motion of various parts of the body, including the torso, arms, and legs, produces a characteristic signature. Combined with idiosyncrasies of carriage, heat will uniquely impact a surrounding sensor field, even while the subject follows a prescribed path.

The pyroelectric infrared (PIR) sensor is a high performance IR radiation detector and its low cost and low power consumption make it attractive for a wide range of applications. When the temperature changes, electric charge will built up on the sensing element by virtue of pyroelectricity. The resulting charge translated into a current that a current-to-voltage transductance amplifier converted to a voltage signal. By measuring the sensor response generated by a person walking within the field of view of a PIR sensor module, we can model this response data to a code vector that uniquely identifies the person.

We have developed two PIR feature-generating sensor systems. One system is analog, the other digital, and both are derived from the signals generated by humans crossing the detection areas. We successfully demonstrate that by selecting suitable sensor configurations and feature extraction/training algorithms, the sensor systems are capable of performing human identification.



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