

在轉換空間中識別人類室內活動

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摘要



從串流視訊影像資料中識別人類活動有相當多應用，例如人機介面、安全監控系統、居家看護等等。在視訊影像資料處理上影像的維度相當大，並且造成辨識上的困難。因此，這些影像資料通常會利用某些資料轉換以縮減維度，例如主成份分析（principle component analysis）、小波轉換（wavelet）等等。

本論文的目的是提供一個能夠自動監控、追蹤並且辨識人類活動的系統。我們利用資料轉換將影像轉換至標準空間，提供一個能夠在視訊影像中辨識人類活動的系統。在我們的系統中，每一影像序列的前景人物會利用一個統計的背景模型而被抽取出來，並以二值化影像代替。背景模型會使用到連續影像的相除（frame ratio）。接著，二值化影像經由特徵空間及標準空間轉換投影至標準空間。最後人類活動的識別在標準空間中完成。我們所提供的系統對每一類的動作僅使用幾個必要且有效的樣板來代表而不使用全部的影像序列，也就是對影像序列作降頻取樣，這麼做的好處是可以降低辨識問題的複雜度、減低運算負載並且增加辨識率。我們提出的這個系統僅僅使用

這些二值化的影像來辨識前景人物的動作，而且沒有參考其他任何資訊例如位置、路徑或速度等等，並有相當高的辨識率。



Recognizing Indoor Human Activity in Canonical Space

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Human activity recognition from video streams has a wide range of application such as human-machine interface, security surveillance, home care system, etc. In video processing, the size of image sequence is usually extremely large so that the human activity is difficult to recognize. Therefore, data transformation is usually taken such as principle component analysis, wavelet, etc.

The objective of this thesis is to provide a human-like system to auto-surveillance and to track people and identify their activities. We present a system for video-based human activity recognition by transforming the images into canonical space. In our system, foreground subject is first extracted as the binary image by a statistical background model using frame ratio which is robust to illumination change, and then transformed by eigenspace and

canonical space transformation, and recognition is done in canonical space. By using several essential templates to represent an activity, our proposed system can recognize the activity of the subject by down sampling the image sequence instead of all consecutive image frames in order to reduce the recognition complexity, decrease the computational load, and improve the recognition performance. Without referring any geographic information such as location, path, and velocity of the subject, our proposed system uses only the binary images of subject to recognize the activity and works very well.



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