Real-Time Hand Gesture Recognition using Motion Tracking

Бу

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Approved by	
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Abstract

Real-Time Hand Gesture Recognition using Motion Tracking

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This paper introduces an attractive alternative human computer interaction interface in future applications, which is the gesture performed by the user. Especially we focus on hand gestures by using its motion representation and several techniques and related works in recent years are reviewed. A gesture recognition system of 10 hand signed digits is proposed in our research, in which we firstly compared different solutions of detecting active hand in a video frame and concluded our skin-subtraction approach, and then locations of hand in a sequence of frames are tracked to extract the feature of motion track. Finally we used the histogram distribution models to recognize each location track as one of ten digits. Our proposed system achieves a recognition rate of 97.33% and also supports for the real-time application.

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LIST OF ABBREVIATIONS

HCI--Human Computer Interaction

VE--Virtual Environment

CV--Computer Vision

DOF--Degree of Freedom

MCP--Metacarpophalangeal

IP--Interphalangeal

CMC--Carpometacarpal

TM--Trapeziometacarpal

MHI--Motion History Image

PCA--Principle Component Analysis

HMMs--Hidden Markov Models

KF--Kalman Filtering

FSM--Finite State Machine

MLP--Multilayer Perceptron

TDNN--Time Delay Neural Network

RBFN--Radial Basis Function Network

ANN--Artificial Neural Network

GA--Genetic Algorithm

ASL--American Sign Language

CIE--International Commission on Illumination

PREFACE

In this paper we introduce an attractive research topic on a new generation of human computer interface in modern computer vision systems, which use the hand gesture to interact with environment directly. The background of hand gesture recognition as well as its widespread applications is introduced. Also we discussed some problems and difficulties for the design of a robust and reliable gesture recognition system. Some of proposed works are viewed for each of three stages involved in hand gesture recognition system: gesture modeling, gesture analysis and gesture recognition.

As color cues based and motion cues based solutions are most commonly used for detect object in video frames, we gave a comparison of hand detection in different color spaces and the YCbCr is experimented to be more reliable. Further more, we motivate from the motion cues approach to take inter-frame correlation into consideration and incorporate a modified background subtraction process with skin-color based hand detection in YCbCr space. The best motion track is extracted from multiple track candidates based on their stand derivation measurement. Each track of gesture digit is normalized and smoothed, and encoded into chain code for training models of each gesture class. Compared with Hidden Markov Models (HMMs) tool, we proposed a simple model on the histogram distribution which is shown to be reliable for gesture classification. We achieve a recognition rate of 97.33% out of 300 digit gestures and the computational efficiency is around 60 fps which can support the requirement of real time applications.

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