A Novel System of Wheel Chair With Hand Gesture Recognition Using Mems

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Abstract - Traditional electric-powered wheelchairs are normally controlled by users via joysticks, which cannot satisfy the needs of elderly and disabled users who have restricted limb movements caused by some diseases such as parkingson's disease and quadriplegics. This paper presents a novel hands-free control system for intelligent wheelchairs based on visual recognition of head gestures. The traditional Adaboost face detection algorithm and Camshift object tracking algorithm are combined in our system to achieve accurate face detection, tracking and gesture recognition in real time. It is intended to be used as the human-friendly interface for elderly and disabled people to operate our intelligent wheelchair using their head gestures rather than their hands. Experimental results are given to demonstrate the feasibility and performance of the proposed head gesture based control strategy. The wheelchair is an important way of transfer for handicapped and aged people. Many researchers have been developing intelligent wheelchairs due to the increasing requirement of safer and more comfortable wheelchairs[1], such as Wheelesley, NavChair, SIAMO, Rolland, MAid and so on. Conventional wheelchairs consist of buttons, joystick to carry out various control tasks. With this method, the user needs to be sufficiently agile to reach and operate them. While some of them, especially for the elderly, cannot manipulate the wheelchair with a lack of force or slow response. Intelligent wheelchair is proposed to improve it. Human interface of intelligent wheelchair for easy operation is one of the most popular research issues.

Keywords- Hidden Markov Model; Head Gesture Recognition; Intelligent Wheelchair; Face Detection; Head Gesture Interface; Hands-Free Control; MEMS- Micro Electro Mechanical System; Accelerometer.

I. INTRODUCTION

As an alternative to the joystick control, various input interface such as head movement[2],HandGesture[3],voicecontroller[4],chincontroller,Electromyogram(EMG),Electroencephalogram(EEG)[6] signal controller are developed to improve manipulability, safety and comfortableness. In this paper, we propose a natural human interface based on hand gesture to control the wheelchair motion. For hand gesture recognition system, there are mainly two existing types, i.e., camera-based and MEMS based[12][13]. As the human interface to control wheelchair's motion, camera-based hand gesture recognition is more applied[3][7].

1.2 Markov Processes

Diagram 1 depicts an example of a Markov process. The model presented describes a simple model for a stock market index. The model has three states, Bull, Bear and Even, and three index observations up, down, unchanged. The model is a finite state automaton, with probabilistic transitions between states. Given a sequence of observations, example: up-down-down we can easily verify that the state sequence that produced those observations was: Bull-Bear-Bear, and the probability of the sequence is simply the product of the transitions, in this case $0.2 \times 0.3 \times 0.3$. Hidden Markov Models Diagram 2 shows an example of how the previous model can be extended into a HMM. The new model now allows all observation symbols to be emitted from each state with a finite probability.

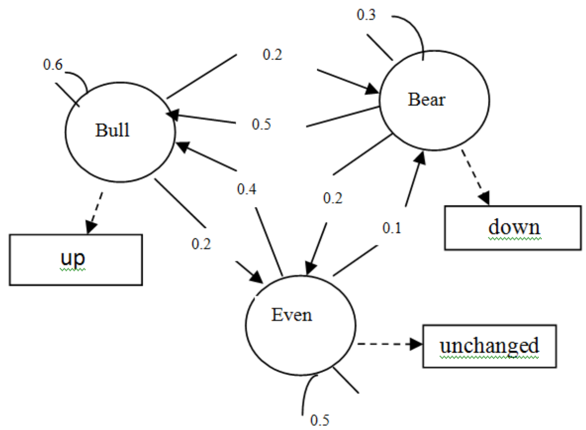

Figure 2: Markov process example

This change makes the model much more expressive and able to better represent our intuition, in this case, that a bull market would have both good days and bad days, but there would be more good ones.

1.3 HMM-based Gesture Recognition

The HMM approach to gesture recognition is motivated by the successful application of hidden markov modeling techniques to speech recognition problems. The similarities between speech and gesture suggest that techniques effective for one problem may be effective for the other as well. First, gestures, like spoken languages, vary according to location, time, and social factors. Second, body movements, like speech sounds, carry certain meanings. Third, regularities in gesture performances while speaking are similar to syntactic rules. Therefore, linguistic methods may be used in gesture recognition. On the other hand, gesture recognition has its own characteristics and problems. To develop a gesture interface, some criteria are needed to evaluate its performance such as meaningful gestures, suitable sensors, efficient training algorithms, and accurate, efficient, on-line/real-time recognition.

1.4 Evaluation

Given a HMM, and a sequence of observations, we'd like to be able to compute P(O|q), the probability of the observation sequence given a model. This problem could be viewed as one of evaluating how well a model predicts a given observation sequence, and thus allow us to choose the most appropriate model from a set.The probability of the observations O for a specific state sequence Q is:

$$P(O|Q,\lambda) = \prod_{t=1}^{T} P(o_t|q_t,\lambda)=b_{q1}(o_1)\times b_{q2}(o_2)\ldots\ldots\ldots b_{qT}(o_T)$$

and the probability of the state sequence is:

$$P(O|\lambda)= \pi_{q1}a_{q1q2}a_{q2q3}\ldots\ldots\ldots a_{qT-1qT}$$

so we can calculate the probability of the observations given the model as:

$$P(O|\lambda) = \sum_Q P(O|Q,\lambda)P(Q|\lambda) = \sum_{q1\ldots qT} \pi_{q1}b_{q1}(O_1)a_{q1q2}b_{q2}(O_2)\ldots\ldots a_{qT-1\,qT}b_{qT}(O_T)$$

This result allows the evaluation of the probability of O, but to evaluate it directly would be exponential in T. A better approach is to recognise that many redundant calculations would be made by directly evaluating equation 13, and therefore caching calculations can lead to reduced complexity. We implement the cache as a trellis of states at each time step, calculating the cached valued (called α) for each state as a sum over all states at the previous time step. α is the probability of the partial observation sequence o1, o2 · · · ot and state si at time t. This can be visualised as in figure 3. We define the forward probability variable:

$$\alpha_t(i)=P(o_1o_2\ldots\ldots o_t,q_t=s_i|\lambda)$$

so if we work through the trellis filling in the values of _ the sum of the final column of the trellis will equal the probability of the observation sequence. The algorithm for this process is called the forward algorithm and is as follows:

1. Intialization

$\alpha_1(i) = \pi_i b_i(o_1), \qquad 1 \le i \le N$

2. Induction

$\alpha_{t+1}(j) = \sum \alpha_t(i)a_{ij} \,|\, b_j(o_{t+1}), \quad 1\le t \le T\text{-}1, \quad 1\le j \le N$

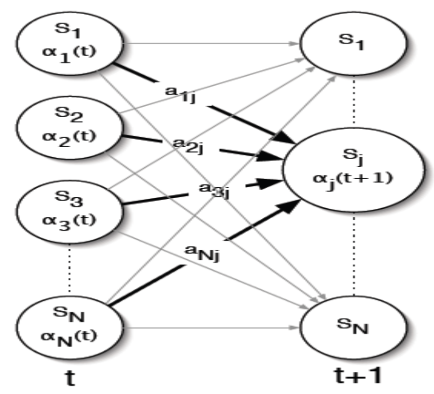

Fig 5: The induction step of the forward algorithm

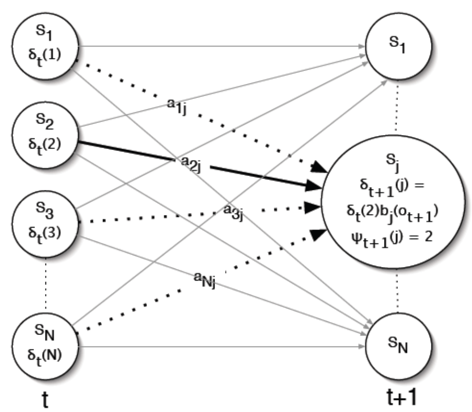

Fig 6: The recursion step of the viterbi algorithm

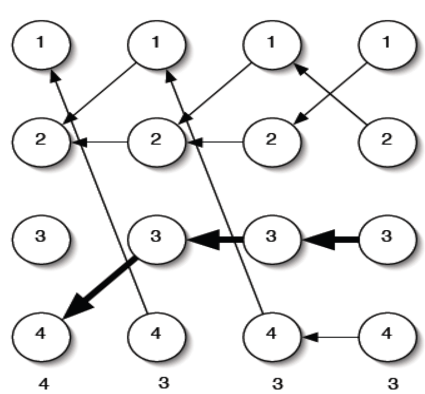

Fig 7: The backtracking step of the viterbi algorithm

The main difference with the forward algorithm in the recursions step is that we are maximizing, rather than summing, and storing the state that was chosen as the maximum for use as a back pointer. The backtracking step is shown in 6. The backtracking allows the best state sequence to be found from the back pointers stored in the recursion step, but it should be noted that there is no easy way to find the second best state sequence.

1.5 Implementing HMMs

When implementing a HMM, floating-point underflow is a significant problem. It is apparent
that when applying the Viterbi or forward algorithms to long sequences the extremely small
probability values that would result could underflow on most machines. We solve this problem differently for each algorithm: Viterbi underflow As the Viterbi algorithms only multiplies probabilities, a simple solution to underflow is to log all the probability values and then add values instead of multiply.In fact if all the values in the model matrices (A,B, _) are stored logged, then at runtime only addition operations are needed. forward algorithm underflow The forward algorithm sums probability values, so it is not a viable solution to log the values in order to avoid underflow. The most common solution to this problem is to use scaling coefficients that keep the probability values in the dynamic range of the machine, and that are dependent only on t. The coefficient c_t is defined as:

$$c_t = 1/\sum_{1=1}^{N} \alpha_t(i)$$

2. DESIGN

2.1 System Work Flow

When the sensing system is switched on, the accelerations in three perpendicular directions are detected by the MEMS sensors and transmitted to a PC via Bluetooth protocol. The sampled gesture sequence data then go through data preprocessing model which filters the environment noise and gravity interference. Then the data sequences are segmented and quantized into 1-D vector. In training phase, the segmented gesture sequences are utilized to train the HMM models. In recognizing phase, the trained HMM model and Bayes method are combined to recognize the gestures from the segmented sample data. Subsequently the motion command is determined by the corresponding recognized gesture. When the motion command is transferred into the wheelchair's motion, S-Curve function is utilized to smooth the velocities between two consecutive motions for the purpose of motion stability. The work flow of the system is shown in Fig.2.

3. IMPLEMENTATION AND RESULTS

3.1 IMPLEMENTATION

This project is to demonstrate that accelerometers can be used to effectively translate finger and hand gestures into computer interpreted signals. For gesture recognition the accelerometer data is calibrated and filtered. The accelerometers can measure the magnitude and direction of gravity in addition to movement induced acceleration. In order to calibrate the accelerometers, we rotate the device's sensitive axis with respect to gravity and use the resultant signal as an absolute measurement. Integrating a single chip wireless solution with a MEMS accelerometer would yield an autonomous device small enough to apply to the fingernails, because of their small size and weight. Accelerometers are attached to the fingertips and back of the hand. Arrows on the hand show the location of accelerometers and their sensitive directions, that the sensitive direction of the accelerometer is in the plane of the hand.The gesture based wheelchair is suitable for the elderly and the physically challenged people who are unfortunate to have lost ability in their limbs due to paralysis or by birth or by old age. Elders find it tough to move inside the house for day to day activities without help or external aid. Our proposed system makes use of a wheelchair that can be used by elderly or physically challenged to move inside the home without difficulty and without external aid

Micro Electro Mechanical Systems (MEMS) are free scale‟s enabling technology for acceleration and pressure sensors. MEMS based sensor products provide an interface that can sense, process or control the surrounding environment. Micro-Electro-Mechanical Systems, or MEMS, is a technology that in its most general form can be defined as miniaturized mechanical and electro-mechanical elements (i.e., devices and structures) that are made using the techniques of micro fabrication.

MEMS-based sensors are a class of devices that builds very small electrical and mechanical components on a single chip. MEMS-based sensors are a crucial component in automotive electronics, medical equipment, hard disk drives, computer peripherals, wireless devices and smart portable electronics such as cell phones and PDAs.The functional elements of MEMS are miniaturized structures, sensors, actuators, and microelectronics, the most notable (and perhaps most interesting) elements are the micro sensors and micro actuators. Micro sensors and micro actuators are appropriately categorized as "transducers", which are defined as devices that convert energy from one form to another. In the case of micro sensors, the device typically converts a measured mechanical signal into an electrical signal.

MEMS technology provides the following advantages: cost-efficiency, low power, miniaturization, high performance, and integration. Functionality can be integrated on the same silicon or in the same package, which reduces the component count.This contributes to overall cost savings. Hence with this project I can save the physically disabled persons who use wheel chairs they can control their wheel chair with their hand movements.

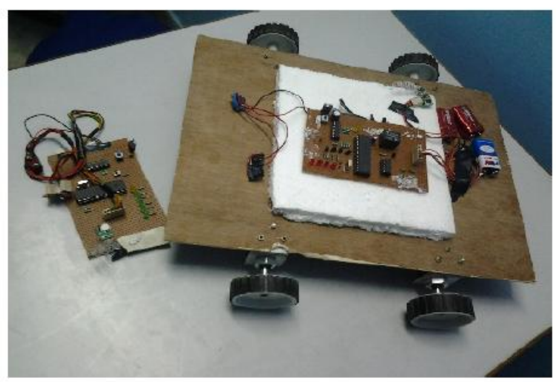

Figure 3.1 Hardware setup for transmitter and receiver

The ADXL202E is a low-cost, low-power, complete 2-axis accelerometer with a digital output, all on a single monolithic IC. It is animproved version of the ADXL202AQC/JQC. The ADXL202Ewill measure accelerations with a full-scale range of 2 g. TheADXL202E can measure both dynamic acceleration (e.g., vibration)and static acceleration (e.g., gravity).The outputs are analog voltage or digital signals whose duty cycles(ratio of pulsewidth to period) are proportional to acceleration.

CONCLUSION AND FUTURE WORK

In this paper we utilize the acceleration data to recognize the hand gestures and then transfer the gesture information which indicates certain motion commands into the wheelchair's smooth motions. It's a try to realize the natural interaction for the older and handicapped with the wheelchair through the hand gestures. On the algorithm of hand gesture recognition, we proposed a real-time gesture segmentation method based on the distance principle which could segment the gesture sequences out of the sensing data automatically.

And then we utilized the trained HMM and Bayes method to judge the gestures online. On the motion control method of wheelchair, to avoid the unsmoothed velocities between two consecutive motions, we adopted the S-curve function to realize the continuous curvature of the velocities. Simulation showed the effectiveness of the recognition method and the realization of the wheelchair's smoothed motion under control. While there still exists a lot of work to do, such as adaptive parameter determination during the gesture segmentation, real wheelchair control under gesture recognition, et al. In the future work, we will focus on these problems and do more experiments to improve and verify the method in real environment

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