GESTURE RECOGNITION USING 3-D ACCELEROMETER

Kasinikota Devika
Assistant Professor
Department of Electronics and Communications Engineering,
St. Martins Engineering College, Dullapally, Secunderabad-500100.

Dr.Anbalagan Anand
Professor
Department of Electronics and Communications Engineering,
St. Martins Engineering College, Dullapally, Secunderabad-500100.

Karra Vineela
Assistant Professor
Department of Electronics and Communications Engineering,
St. Martins Engineering College, Dullapally, Secunderabad-500100.

ABSTRACT: Gesture-based interaction, as a natural way for human-computer interaction, has a wide range of applications in ubiquitous computing environment. This paper presents an acceleration-based recognition of gesture approach, called FDSVM (Frame-based Descriptor and multi-class SVM), which needs only a wearable 3-dimensional accelerometer. With FDSVM, firstly, the acceleration data of a gesture is collected and represented by a frame-based descriptor, to extract the discriminative information. Then a SVM-based multi-class gesture classifier is built for recognition in the nonlinear gesture feature space. Extensive experimental results on a data set with 3360 gesture samples of 12 gestures over weeks demonstrate that the proposed FDSVM approach significantly outperforms other four methods: Naive Bayes, DTW, HMM and C4.5 . In the user-dependent case, FDSVM achieves the recognition rate of 99.38% for the 4 direction gestures and 95.21% for all the 12 gestures. In the user-independent case, it obtains the recognition rate of 98.93% for 4 gestures and 89.29% for 12 gestures. Compared to other accelerometer-based gesture recognition approaches reported in literature FDSVM gives the best results for both user-dependent and user-independent cases.

Keywords: *DTW, SVM, Gesture, Acceleration.*

I.Introduction

As computation is getting to play an important role in enhancing the quality of life, more and more research has been directed towards natural human-computer interaction. In a smart environment, people usually hope to use the most natural and convenient ways to express their intentions and interact with the environment. Button pressing, often used in the remote control panel, provides the most traditional means of giving commands to household appliances. Such kind of operation, however, is not natural and sometimes even inconvenient, especially for elders or visually disabled people who are not able to distinguish the buttons on the device. In this regard, gesture-based interaction offers an alternative way in a smart environment. Most of previous work on gesture recognition has been based on computer vision techniques. However, the performance of such vision-based approaches depends strongly on the lighting condition and camera facing angles, which greatly restricts its applications in the smart environments. Suppose you are enjoying movies in your home theater with all the lights off. If you intend to change the volume of TV with gesture, it turns out to be rather difficult to accurately recognize the gesture under poor lighting condition using a camera based system. In addition, it is also uncomfortable and inconvenient if you are always required to face the camera directly to complete a gesture. Gesture recognition from accelerometer data is an emerging technique for gesture based interaction, which suits well the requirements in ubiquitous computing environments. With the rapid development of the MEMS (Micro Electrical Mechanical System) technology, people can wear/carry one or more accelerometer-equipped devices in daily life, for example, Apple iPhone, Nintendo Wiimote. These wireless-enabled mobile/wearable devices provide new possibilities for interacting with a wide range of applications, such as home appliances, mixed reality, etc. The first step of accelerometer-based gesture recognition system is to get the time series of a gesture motion. Previous studies have adopted specific devices to capture acceleration data of a gesture. For example, TUB-Sensor Glove can collect hand orientation and acceleration, and finger joint angles. Tsukada designed a finger based gesture input device with IR transmitter, touch sensor, bend sensor and acceleration sensor. Mäntyjärviput a sensor box into a phone in order to detect 3-axis acceleration of users' hand motion. Now most accelerometers can capture three-axis acceleration data, i.e. 3D accelerometers, which convey more motion information than 2D accelerometers. They have been embedded into several commercial products such as iPhone and Wiimote. This paper employs Wiimote as the gesture input device for experimental set-up and performance evaluation.

II.GESTURES

Gestures are an important aspect of human interaction, both interpersonally and in the context of man-machine interfaces.

- A gesture is a form of non-verbal communication in which visible bodily actions communicate particular messages, either in place of speech or together and in parallel with words.

- Gestures include movement of the hands, face, or other parts of the body.

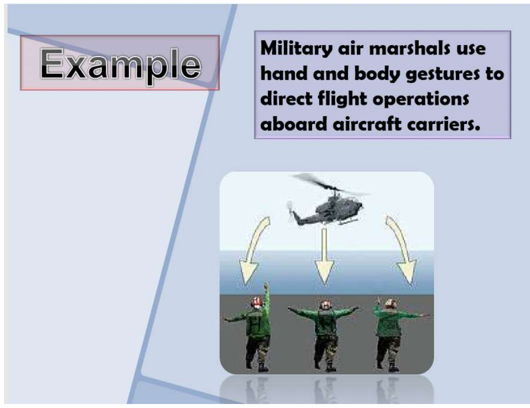

Figure 2.1: An example showing gesture recognition

Types of gestures:

- Gesticulation: Spontaneous movements of the hands and arms that accompany speech.
- Language-like gestures Gesticulation that is integrated into a spoken utterance, replacing a particular spoken word or phrase.
- Pantomimes: Gestures that depict objects or actions, with or without accompanying speech.
- Emblems: Familiar gestures such as V for victory, thumbs up, and assorted rude gestures.
- Sign languages: Linguistic systems, such as American Sign Language, which are well defined.

What is Gesture Recognition?

Interface with computers using gestures of the human body, typically hand movements. Gesture recognition is an important skill for robots that work closely with humans. Gesture recognition is especially valuable in applications involving interaction human/robot for several reasons. There are usually two ways to evaluate the performance of the gesture recognition algorithms**: user-dependent** and **user-independent**. Previous work focuses more on user-dependent gesture recognition, in which each user is required to perform a couple of gestures as training/template samples before using the system. One of the solutions to this problem is to reduce the user efforts in training by adding artificial noise to the original gesture data to augment the training data. The user independent gesture recognition does not require a user to enroll any gesture samples for the system before using it, where the model for classification has been well trained before and the algorithm does not depend on users. The user-independent gesture recognition is more difficult than the user-dependent one since there is much more variation for each same gesture.

III.3-D ACCELEROMETER

A **3-D accelerometer** is a device that measures proper acceleration. Proper acceleration, being the acceleration (or rate of change of velocity) of a body in its own instantaneous rest frame, is not the same as coordinate acceleration, being the acceleration in a fixed coordinate system. For example, an accelerometer at rest on the surface of the Earth will measure an acceleration due to Earth's gravity, straight upwards (by definition) of $g \approx 9.81$ m/s^2. By contrast, accelerometers in free fall (falling toward the centre of the Earth at a rate of about 9.81 m/s^2) will measure zero.

Accelerometers have multiple applications in industry and science. Highly sensitive accelerometers are components of inertial navigation systems for aircraft and missiles. Accelerometers are used to detect and monitor vibration in rotating machinery. Accelerometers are used in tablet computers and digital cameras so that images on screens are always displayed upright. Accelerometers are used in drones for flight stabilisation. Coordinated accelerometers can be used to measure differences in proper acceleration, particularly gravity, over their separation in space; i.e., gradient of the gravitational field. This gravity gradiometer is useful because absolute gravity is a weak effect and depends on local density of the Earth which is quite variable.

Figure 3.1: 3-D Accelerometer

Single and multi-axis models of accelerometer are available to detect magnitude and direction of the proper acceleration, as a vector quantity, and can be used to sense orientation (because direction of weight changes), coordinate acceleration, vibration, shock, and falling in a resistive medium (a case where the proper acceleration changes, since it starts at zero, then increases). Micro-machined micro-electromechanical systems (MEMS) accelerometers are increasingly present in portable electronic devices and video game controllers, to detect the position of the device or provide for game input.

Recognition of Gesture using 3-D Accelerometer Technology:

To evaluate the system, we collected a gesture acceleration data set with 12 gestures of ten individuals. We adopted Wiimote, the controller of Nintendo Wii equipped with a 3D accelerometer, to acquire gesture acceleration data. It can transmit users' gesture motion acceleration data via Bluetooth. The start and end of a gesture were labeled by pressing the A button on the Wiimote during data acquisition.

Figure 3.2: **Acquisition devices of Gesture recognition Data**

Wiimote: It is a motion sensing capability which allows the user to interact with and manipulate the items on screen via gestures recognition and pointing, using Accelerometer and Optical Sensor technology.

In order to evaluate our gesture recognition algorithm, we choose three kinds of typical gestures: 4 direction gestures, 3 shape gestures, 5 one-stroke alphabet letters (the other 4 one-stroke letters, "O, L, U, M", are not included since 'O' is similar to CIRCLE, 'L' is similar to RIGHT-ANGLE, 'U' is similar to 'V', and 'W' is close to 'M'), as illustrated in Fig.. These twelve gestures are divided into four groups (cf. Table 1) for evaluating the recognition performance. The first group is for direction gestures, the second for direction gestures plus shape gestures, the third is for one stroke letters, and the last group is for all 12 gestures.

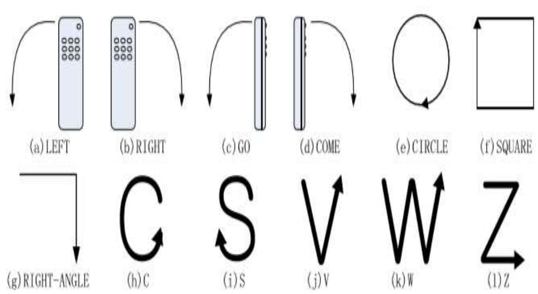

Figure 3.3: Twelve gestures in the data set. (a) – (d) describe the gestures to swing the remote to left, right, forward or backward centered at the bottom point of the remote. (e) – (l) describe the gestures to draw a shape or letter

Ten people participated in the data collection, including two female and eight male students aged between 21 and 25. Each student was asked to perform each gesture for 28 times over two weeks, namely 336 gesture samples in total. Every 12 different gestures performed sequentially was regarded as one set of gesture data. In order to consider variability of user performance, a participant was not allowed to perform more than two sets each time and not more than twice per day. The following table shows twelve gestures that are divided into 4 groups for extensive evaluation:

S.No.	Group Name	Included Gestures
1	Direction	LEFT, RIGHT, GO, COME
2	Direction + Shape	LEFT, RIGHT, GO, COME, CIRCLE, SQUARE, RIGHTANGLE
3	One-stroke Letter	C, S, V, W, Z, CIRCLE(O), RIGHT-ANGLE(L)
4	All	LEFT, RIGHT, GO, COME, CIRCLE, SQUARE, RIGHTANGLE, C, S, V, W, Z

Tabel 1: Twelve gestures are divided into 4 groups for extensive evaluation

User-Dependent Gesture Recognition:

In this experiment, to demonstrate the performance of our method, we compare it with four methods: decision tree C4.5, DTW, Naive Bayes and the HMM algorithm implemented by the package WiiGee (which is an HMM-based method derived. We employed the implementation of C4.5 by Quinlan and the WiiGee system developed by the authors for comparison purpose.

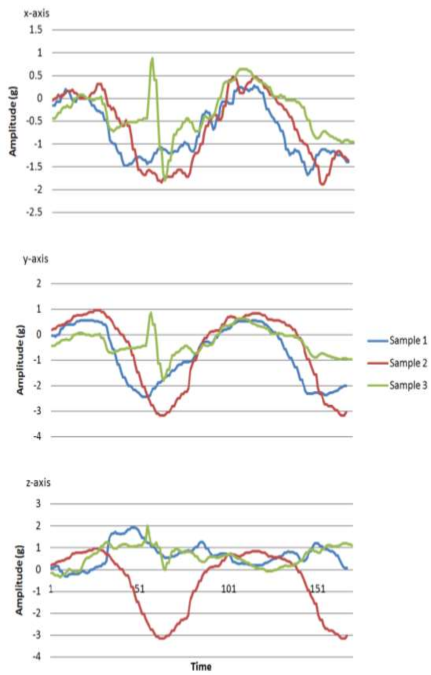

Figure 3.4: Variation of a gesture for the same person. The three acceleration samples are from the gesture 'W' of the same person, shown in x-axis, y-axis, z-axis respectively. The three samples were performed at different time.

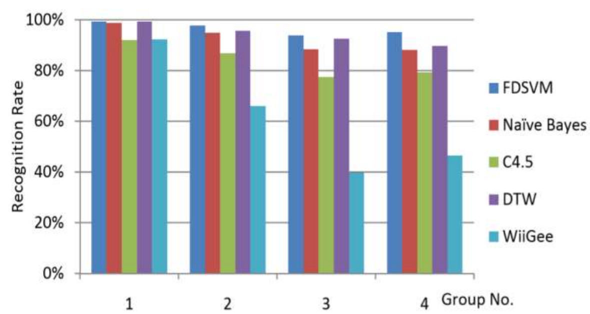

Figure 3.5: The experimental results for the user-dependent case

We carried out the experiments and comparison tests on the four groups of data set respectively. The comparison results are shown in Fig. When recognizing the four gestures of Group 1, the recognition rate of the five approaches are all more than 90%, where our proposed FDSVM achieved 99.38%. From the figure, the performance of WiiGee decreases significantly when the number of gesture type increase. In contrast, our FDSVM method performs well even in recognizing all the 12 gestures, with the recognition rate of 95.21%. DTW is slightly better than Naïve Bayes while it is still outperformed by our FDSVM for Group tests 2/3/4.

User-Independent Gesture Recognition:

User-independent case means that the system is well-trained before users use it. Such implementation avoids users' efforts to perform several gestures as training data. The results of user-independent gesture recognition test and comparison are shown in Fig. Obviously, the recognition rate of user-independent gesture recognition is lower than that of user-dependent one. Our FDSVM significantly outperforms the others. It obtains the recognition rate of 98.93% for 4 gestures of Group 1 and 89.29% for 12 gestures of Group 4. DTW and Naïve Bayes achieve recognition rate of 99.20% and 98.30% respectively for Group 1, very close to the performance of FDSVM. However, our FDSVM significantly outperforms DTW and Naïve Bayes for 7 gestures of Group 2, 7 gestures of Group 3, and 12 gestures of Group 4. The result reveals that our FDSVM has good generalization capability when the gesture type increases.

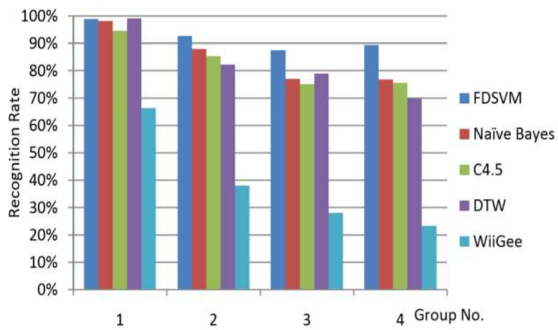

Figure 3.6: The experimental result for the user-independent case

Advantages:

- Simple, fast and easy to implement.
- Can be applied on real systems
- Speed and sufficient, reliable for many applications

Applications:

- Pedometer: Motion Sensing
- Portable Handheld: Text Scrolling
- Navigation and Dead Reckoning: E-Compass Tilt Compensation
- Gaming:Tilt and Motion Sensing,Event Recorder
- Laptop PC:Free fall Detection
- Cell Phone:ImageStability,TextScrolling,MotionDialing
- Robotics:Motion Sensing
- Portable Handheld:Text Scrolling

Results:

In this paper, an acceleration based gesture recognition method, called FDSVM, is presented and implemented. Different from the popular accelerometer-based gesture recognition approaches in the literature such as HMM and DTW, which don't include feature extraction explicitly this paper proposes a frame based gesture descriptor for recognition, which combines spectral features and temporal feature together.

A Framework for Hand Gesture Recognition Based on Accelerometer and EMG Sensors. For gesture-based control, a real-time interactive system is built as a virtual Rubik's cube game using 18 kinds of hand gestures as control commands.

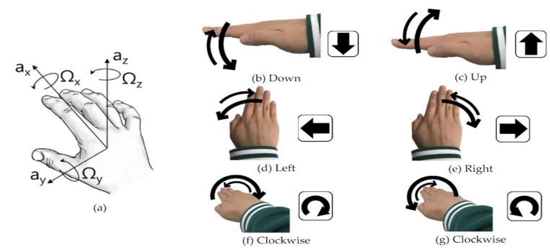

Figure 3.7: Resulting a framework for hand Gesture

IV.Conclusion

In this paper, an accelerometer-based gesture recognition method, called FDSVM, is presented and implemented. Different from the popular accelerometer-based gesture recognition approaches in the literature such as HMM and DTW, which don't include feature extraction explicitly this paper proposes a frame-based gesture descriptor for recognition, which combines spectral features and temporal features together. This explicit feature exaction stage effectively reduces the intra-class variation and noise of gestures. To tackle the issue of high nonlinearity of the gesture feature space, a multiclass SVM-based gesture classifier is built. The extensive experiments on a data set with 3360 gesture samples of 12 gestures over time demonstrate that our approach FDSVM achieves the best recognition performance both in the user-dependent case and in the user-independent case, exceeding other four methods, DTW, HMM, Naïve Bayes and C4.5. In particular, the perfect user-independent performance of FDSVM on the large dataset, the high recognition rate of 98.93% for 4 gestures and 89.29% for 12 gestures hints us that the practical user-independent gesture recognition could be possible in the near future. The future work is planned in three folds: new applications of the accelerometer based gesture recognition, new approaches to improve the user-independent performance, and the continuous gestures recognition.

References:

1. Schlomer, T., Poppinga, B., Henze, N., Boll, S.: Gesture Recognition with a Wii Controller. In: International Conference on Tangible and Embedded Interaction (TEI 2008), Bonn Germany, Feburary 18-20, pp. 11–14 (2008) .

2. Tsukada, K., Yasumura, M.: Ubi-Finger: Gesture Input Device for Mobile Use. In: Proceedings of APCHI 2002, vol. 1, pp. 388–400 (2002).

3. Sawada, H., Hashimoto, S.: Gesture Recognition Using an Accelerometer Sensor and Its Application to Musical Performance Control. Electronics and Communications in Japan Part 3, 9–17 (2000) .

4. Mäntylä, V.-M., Mäntyjärvi, J., Seppänen, T., Tuulari, E.: Hand Gesture Recognition of a Mobile Device User. In: Proceedings of the International IEEE Conference on Multimedia and Expo., pp. 281–284 (2000).

5. Mäntyjärvi, J., Kela, J., Korpipää, P., Kallio, S.: Enabling fast and effortless customization in accelerometer based gesture interaction. In: Proceedings of the 3rd International Conference on

Mobile and Ubiquitous Multimedia (MUM 2004), October 27-29, pp. 25–31. ACM Press, New York (2004).