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Remote Gesture Control Using HMM Classifier Based on Electric Potential Sensors

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Abstract

In this paper, HMM based non-contact gesture recognition using EPS(Electric Potential Sensor) is implemented, First, EMI(Electro-Magnetic Interference) in ELF(Extremely Low Frequency) band from surrounding environments is minimized through EMI removing process as well as preprocessing. Hand gesture recognition algorithms applied for smart TV remote control are presented and evaluated. Our proposed cumulative electric potential based "left to right model" is implemented and its performance is compared to that of an ergodic model based directional vectors. Also, we implement the HMM by finding the optimal numbers of states and quantization, and then compare its performance with other typical algorithms.

Keywords: *EPS, Gesture control, HMM, ELF, IR*

1. Introduction

Recently, smart devices like TVs and phones can provide new application services and frameworks using embedded or exterior sensors, which leads to develop extracting, measuring, and analyzing techniques based on multi-modal information such as bio-signals, gesture, voice, and image signals.

However, it is almost impossible to embed all those sensors into the limited space of a mobile smart device. Therefore, it is highly demanded to new UI and UX technology to integrate many required sensors into a smart device to meet increasing user or required sensors into a smart device to meet increasing user or IoT(Internet of Things) demands. Non-contact based intuitive input systems are growing in current contact based input systems market like touch screens. IR(InfraRed) sensors and EPS(Electric Potential Sensor) are typical attracting alternatives in that category.

Especially, EPS was studied and developed in early stage for measuring contact based bio-signals such as electrocardiogram or pulse beat, but Sussex University research team opened possibility to extend its usage to new territory; non-contact bio-signal detection, position and proximity detection which demonstrated its superiority to contemporary image-based detection techniques through the patent registered in 2012 [1].

EPS based remote sensing systems have clear advantages in cost, size, consumed power, and speed compared to a IR based system which is one of prevailing image sensing techniques, as shown in Table 1.

First, the EPS based sensing system produce only two-byte data per channel and requires simpler preprocessing cost because its main noise source is 60Hz PLN(Power Line Noise). Meanwhile, IR based system needs not only to process 300,000 bytes per frame in case of 640x480 resolution, but also to eliminate noise on illumination and background image, which leads the system complex to implement.

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Second, the EPS sensor's cost in case of mass purchase is less than 1$ and its size is 10.5 x 10.5 x 3 mm while that of an IR sensor is about 100$ in case of SR40000 module and its size is 65 x 65 x 68 mm.

Table 1. Comparison of EPS and Typical Image based Sensors

	CMOS	IR	EPS
Data per frame(byte)	~1,300,000	~ 300,000	8
Size(mm)	65 x 65 x 68	65 x 65 x 68	10.5 x 10.5 x 3
Cost per unit($)	~10	~100	~1
Power(mA)	325	100	8
Speed(fps)	30	30 ~ 60	5,000

Third, an EPS sensor needs less 2 mA per unit while the counterpart does about 100mA which makes its application to devices like smart phones unacceptable. Finally, the maximum sensing speed of an EPS sensor is 5 KHz while the counterpart is 30 fps in general. Table 1 shows the summary of comparison among CMOS image sensor, IR sensor, and EPS.

2. Discussion

2.1. 4-channel EPS based Non-Contact Gesture Recognition

Our proposed EPS based non-contact gesture recognition process consists of 4-stage processing, EMI elimination, preprocessing, gesture detection, and gesture classification. In EMI elimination stage, we remove EMI in ELF-band through techniques such as grounding, shielding using metal fiber, and filtering [2]. Next, an adaptive Kalman filtering technique combined with 60Hz PLN noise elimination process minimizes remaining fine noise. Then preprocessing stage is followed for initializing the electric potential voltages of all four sensors to zero. The output signals from the sensors are normalized such that the maximum and minimum values become +1 and −1, respectively.

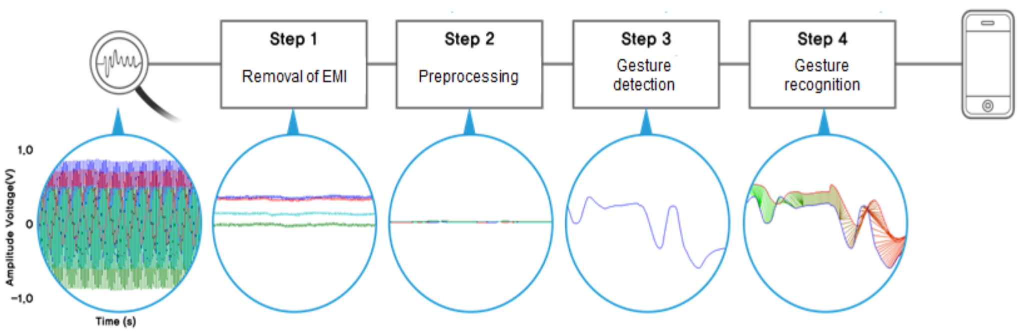

Figure 1. EPS based non-contact Gesture Recognition Process

2.2. Proposed Cumulative Electric Potential Based HMM

Gesture detection problem using EPS is a challenging work because signals have be to compensated according to the position and direction of a moving hand. In our experiment, we limit the distance within 1 m between the sensors and a moving object which is a human hand. A set of 10 hand gestures are used to control a smart device as shown in Table 2. Each of three persons takes 100 hand movements per each gesture. Total 3000 gesture data are categorized to two groups, one group (20%) for training and the other (80%) for testing and classifying.

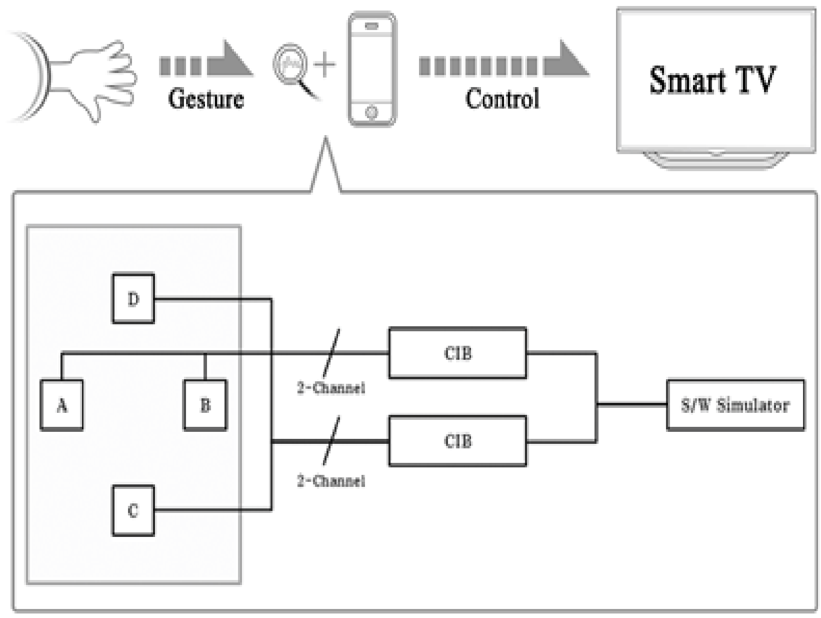

Figure 2. Arrangement of 4-channel EPS Array

Table 2. Proposed Gesture Scenario

No	Gesture	No	Gesture
1		6	
2		7	
3		8	
4		9	
5		10	

HMM based gesture recognition process is divided into four steps; mapping, quantization, HMM modeling, and classifying. The mapping step collects data A to D coming out from four sensors after preprocessing and gesture detection, and performs subtractions, A-B and C-D, and finally maps them into two-dimension gesture data, $G_t(x, y)$, as shown in Figure 3.

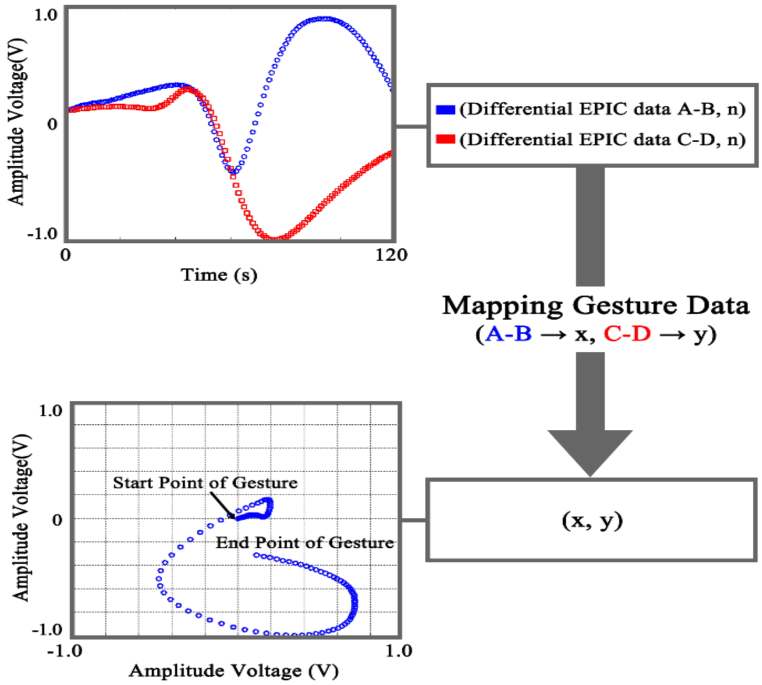

Figure 3. Proposed Mapping Method of EPS Data

The next step is to make quantization so that real values can be converted to integer values, which makes easier to implement the HMM classifier. $G_t(x,y)$ is mapped to M numbers of symbols V in Equation 1 and finally mapped to observation matrix, $O_t(V_x,V_y)$. T denotes the length of gesture data and total 120 data are obtained for two seconds, 60 per second.

$$V = (v_1, v_2, \cdots, v_M) \tag{1}$$

$$O = (O_1, O_2, \cdots, O_T) \tag{2}$$

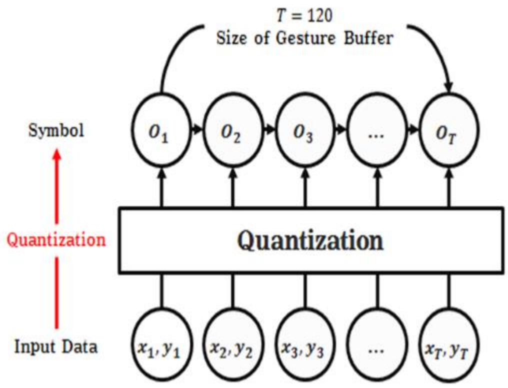

Figure 4. Relation Diagram of Gesture Data and Observation Symbols

In the third stage, HMM model, $\theta = (A, B, \pi)$ is developed where A denotes the state transition probability, B observation probability, π initial state probability [4]. Image based HMM classifier is usually implemented as a direction vector based ergodic model. However, the gesture date from EPS do not have clear directional information. Thus, we propose so called “left-to-right model” as shown in Figure 6.

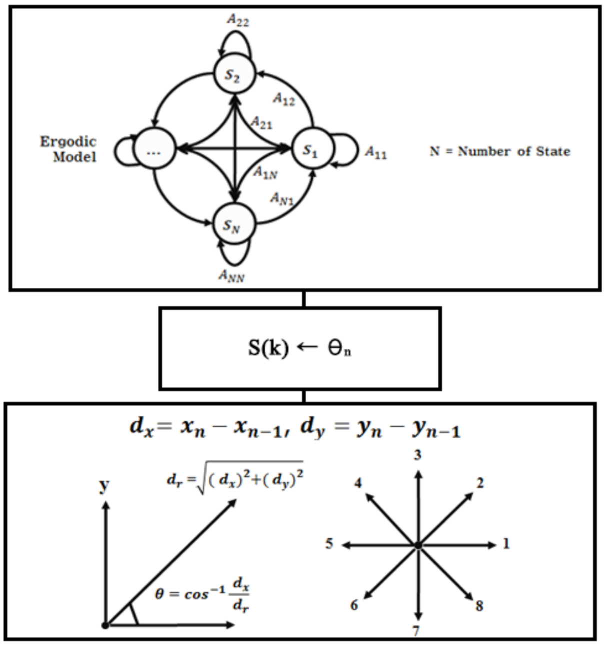

Figure 5. Implemented Directional Vector based Ergodic Model

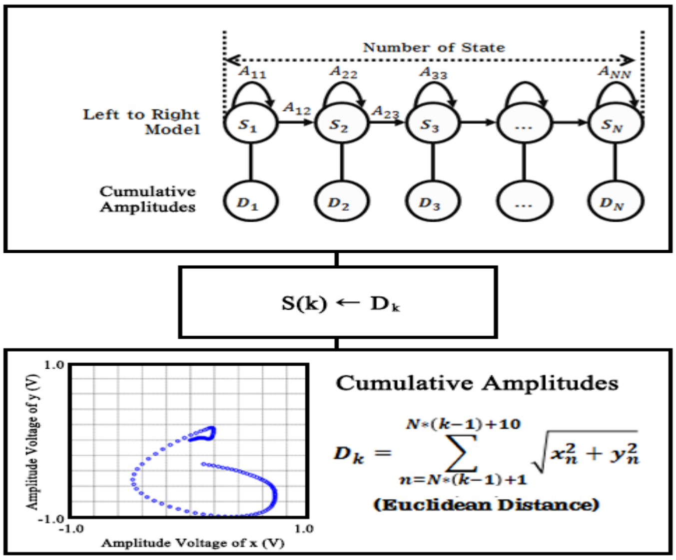

Figure 6. Proposed Cumulative Electric Potential based Left-To-Right Model

Before implementing the HMM classifier, we define the state sequence Q , the state S , and N the total number of states in Equations 3 and 4. The cumulative electric potential value is calculated in Equation 5. In turns, the corresponding state is decided.

$$Q = (q_1, q_2, \cdots, q_T) \tag{3}$$

$$S_i = (s_1, s_2, \cdots, s_N) \tag{4}$$

$$\sigma = \sum_{t=1}^{120} (x_t^2 + y_t^2) \quad (5)$$

State transition probability, A, is the probability that the previous state is transferred to the current state as Equation 6. The summation of all of the state transition probabilities is equal to 1.

$$A_{ij} = P(Q_t = S_j | Q_{t-1} = S_i), \sum_{j=1}^{N} A_{ij} = 1 \quad (6)$$

Observation probability, B, is the probability that a symbol is observed in the current state as in Equation T. The summation of all of the observation probability is equal to 1.

$$B_i(V_k) = P(Q_t = V_k | Q_t = S_i), \sum_{k=1}^{M} B_i(V_k) = 1 \quad (7)$$

Initial state probability, π, denotes the probability of a state before the hand gesture starts as shown in Equation 8. Since the cumulative potential starts with value of zero in our proposed model, $\pi = (1,0,\cdots,0)$.

$$\pi = P(Q_1 = S_i) \quad (8)$$

In the final stage in the proposed process, we use the Baum-Welch algorithm for gesture classification, calculate and accumulate two dimensional probability data, and produce the maximum probability [5]. Since the ideal numbers of states and symbols are unknown, optimal N and M values must be found such that the best result can be produced through experiment.

2.3. Experiments and Results

In this paper, the most appropriate model is found and implemented through analysis of the HMM performance in function of N and M. Table 3 shows performance results in CCR(Correct Classification Rate) of two different HMM classifiers, an ergodic model and the proposed model. The proposed model demonstrates the best result when the number of N and M is 100. Also it is shown in the table that the proposed model produces average 8.1% better CCR than a typical ergodic model.

In the experiment, we also implement the other typical classifying algorithms; Bayesian, K-NN, and DTW(Dynamic Time Warping). Also the performance of our proposed HMM classifier is compared with those of the three approaches. All of the experimental results justify that our proposed HMM based classifier has a clear advantage over other conventional approaches.

Table 3. Comparison in CCR between the Ergodic Model and the Proposed Model

No. of N and M	Ergodic model	Proposed model
5	54.1%	76%
10	60.1%	84.3%
20	64.5%	88.6%
30	73.1%	90%
40	72.4%	91.2%

50	76.3%	91.5%
100	83.9%	92%
200	87.3%	91.5%
400	88.3%	89.6%

Table 4. Comparison in CCR among the Proposed HMM and other Typical Approaches

Classifier	CCR
Bayesian	67%
K-NN	88%
DTW	84%
HMM	92%

3. Conclusion

In this paper, we propose and implement the EPS based non-contact gesture recognizer using HMM classifier. We justified the validity of the proposed model through experiments comparing performance results with other promising classifying algorithms. Experimental results shows the best classification rate is obtained when the number of N and M is 100. Our study demonstrates not only the promising feasibility of the EPS based remote control system applied to smart devices, but the future challenges in this work such as necessity of further exploration in finding better and more robust solution.

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