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A Study of Behaviors Recognition Method using Smartphone Sensors

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Abstract: The SVM (Signal Vector Magnitude) values used in most behavior recognition studies are appropriate for recognizing dynamic behavior but difficult to recognize static behavior. Therefore, we introduced "Polar angle" to recognize static behavior. This is the method of using the angle between the measuring sensor and the axis of gravity acceleration opposite direction. In this study, we propose a method using SVM and angle to effectively recognize dynamic behavior and static behavior. Experimental results show that the proposed method achieves an average of 95.55% accuracy.

Key words: Behavior recognition, falling, polar angle, IoT, accuracy, method

INTRODUCTION

Recently, researches on IoT (Internet of Things) have been actively conducted due to the development of sensors and communication technologies. IoT uses various sensors to measure human behavior or to measure temperature, humidity, etc. to provide various services. Among them the service combining Healthcare with IoT is increasing. The IoT healthcare market forecast for 2017, market research firm market and market, predicts that the IoT healthcare market will grow from $41.2 billion in 2017 to $158 billion in 2022. One of these IoT healthcare technologies is behavior recognition technology.

Behavior recognition technology is a technology that recognizes the behavior in human daily life. Behavior recognition is one of the important technologies related to health (Lara and Labrador, 2013). Most of the behavior recognition techniques use various sensors such as acceleration sensor, gyroscope sensor, pressure sensor and image sensor (Lotfi *et al*., 2012). Recently, sensors built in smart phones are mainly used (Kim and Kim, 2014). Acceleration sensors are used primarily to recognize the behavior. SVM based on the gravitational acceleration value of the acceleration sensor (Yang, 2009). The transformed data are classified using threshold, mean and standard deviation.

However, it is difficult to recognize static behavior. Therefore, to solve this problem, we propose a method of recognizing human's static behavior using "Polar angle". In this study, SVM value and "Polar angle" are obtained by collecting data of acceleration sensor built in the smartphone. We use these data to recognize the behavior.

Literature review

Behavior recognition technology: Behavior recognition is recognizing ADL (Activities of Daily Living). Most behavior recognition technologies use the sensor to collect sensor data and process data to obtain behavior data (Lotfi *et al*. 2012). The SVM value is obtained from the acceleration sensor and classified into behavior data according to the threshold of the SVM value (Kim and Kim, 2014). Figure 1a shows the SVM value graph when falling after running. Figure 1b shows a case when standing after running. As in Fig. 1a, b, it is difficult to recognize the static state with only the SVM value (Rohan, 2017).

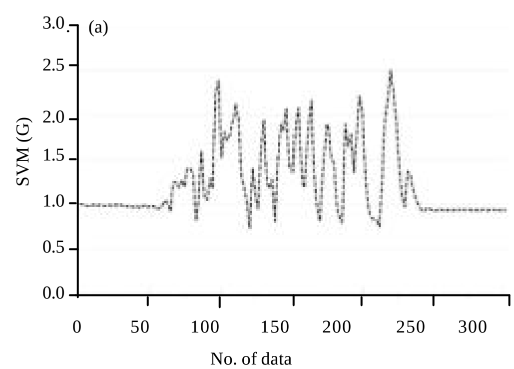

Fig. 1: Continue

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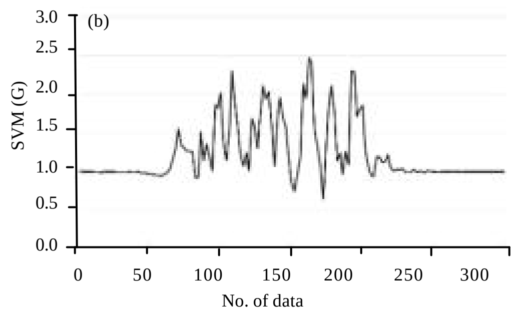

Fig. 1: SVM Grapha): Running, falling, prone position and b) Running, standing

MATERIALS AND METHODS

Polar angle: Static states in ADL include “Standing”, “Sitting” and “Prone Position”. Dynamic behaviors include “Walking”, “Running” and “Falling”. The static states defined in this study are as follows.

- Prone position: prone state after falling
- Sitting: falling cause kneeling or sitting state
- Standing: standing state

In this study, polar angle (θ) is introduced to solve the problem that it is difficult to recognize the static state only by the SVM value. This θ refers to the angle from the positive direction of the z-axis in the three-dimensional coordinate plane of x-z to the origin and an arbitrary straight line. In this study, θ refers to the angle between the origin (center) and an arbitrary straight line (y-axis of the acceleration sensor) from the direction opposite to the gravitational acceleration.

Figure 2 shows polar angle (θ) as a figure. The formula for obtaining θ is shown in Eq. 1:

$$\theta_{radiation} = \cos^{-1}\left(\frac{y}{\sqrt{x^2+y^2+z^2}}\right) \tag{1}$$

Since, the angle derived from Eq. 1 is a radian value, it is converted into a degree value using Eq. 2:

$$\theta_{degree} = \theta_{radiation} \times \frac{180}{\pi} \tag{2}$$

Figure 3a, b show the y-axis values of the acceleration sensors in Fig. 1a and b as θ. As shown in Fig. 3a, b, the “standing” state’s angle is about 0°. On the contrary when it is “Prone Position” state’s angle, it is about 90°. A static state can be recognized using θ.

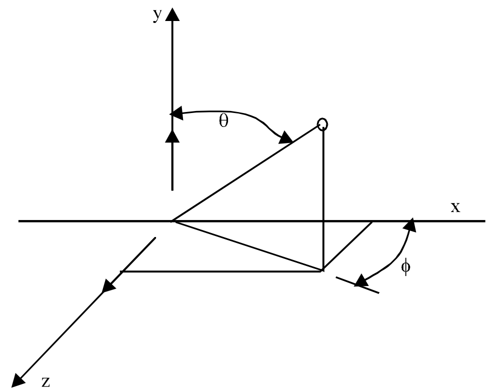

Fig. 2: Diagram Conceptual of θ

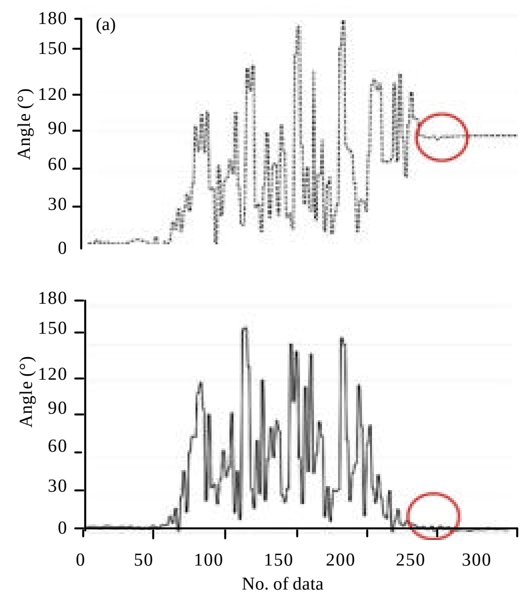

Fig. 3: θ graph: a) Running, falling, prone position and b) Running, standing

Method and decision table: In order to recognize the behavior by introducing the proposed θ in this study, the acceleration sensor data built in the smartphone was collected. The data collection interval is set to 20 msec and collected 50 times/sec. Behavior recognition basically recognizes dynamic behavior according to the threshold value and range of the SVM value. In addition, if the SVM value is 1G, a static behavior is recognized according to θ. Table 1 summarizes the SVM values used in this study and the range, threshold and average of θ.

Each behavior was measured 30 times for 3 sec to tabulate a decision table. As shown in Table 1, the SVM value threshold and the θ value are similar in the case of “Running” and “Falling”. Generally, it takes <0.5

Table 1: Decision table

	Static state					
	Prone position		Sitting		Standing	
Behavior	Range	Mean	Range	Mean	Range	Mean
SVM(G)	0.9791~1.0208	0.9999	0.9891 ~ 1.0153	1.0022	0.9999~1.0049	1.0024
θ(°)	80~95	89.9217	39~68	58.8532	0~15	5.8217
Dynamic behavior						
Behavior	**Walking**		**Running**		**Falling**	
	Range	Threshold	Range	Threshold	Range	Threshold
SVM(G)	0.6914~1.6984	1.4411	0.4819~2.4717	2.0059	0.4794~2.4921	2.0562
θ (°)	3.47~61.01	48.8585	9.32~171.39	103.9234	13.33~176.06	128.0029

sec for "Falling". Therefore, a window is placed for 0.5 sec to move for 0.25 sec. In this study, the static state is recognized according to the range of θ when the static state continues for more than 0.5 sec after dynamic behavior.

Behavior algorithm: Algorithm 1 is a behavior algorithm based on the decision table. Acceleration sensor data is collected in 20 msec units x-z are measurement data of the x-z-axes of the acceleration sensor. These values are converted to SVM and θ. The count is set to increase by 1 in order to move the window by 250 milliseconds every 500 m sec. t means time.

Algorithm 1; Behavior algorithm:

begin: t = 0; do{
}while (t%500! = 0)
calculate SVMavg
t = time (ms) if ($SVM_t \geq 2$ or $|SVM_t-1| \leq 0.05$){
if (θt≥100°){
x = ACCx if ($SVM_{avg}1 = 0.05$)
Falling;
else
Running;
y = ACCy } else {
if ($\theta_t \geq 75°$)
Z = ACCz Prone position
else if ($\theta_t \geq 40°$)
Count = 0 Sitting;
else

$$SVM = \frac{\sqrt{x^2+y^2+z^2}}{9.8}$$

Standing
}else{
Walking;

$$SVM_{avg} = \sum_{count=0}^{25} \frac{SVM_{count}}{25}$$

}

$$\theta = \cos^{-1}\left(\frac{y}{\sqrt{x^2+y^2+z^2}}\right) \times \frac{180}{\pi}$$

}while (input)
end

STANDING
} else{
WALKING
}
}while(input)
end

Table 2: Results table

	Static state			Dynamic behavior		
Parameters	Prone position	Sitting	Standing	Walking	Running	Falling
Static state						
Prone position	30	0	0	0	0	0
Sitting	0	30	0	0	0	0
Standing	0	0	30	0	0	0
Dynamic behavior						
Walking	0	0	0	28	2	0
Running	0	0	0	2	26	2
Falling	0	0	0	0	2	28
Total count	30	30	30	30	30	30
Accuracy (%)	100	100	100	93.3	86.7	93.3

First, increase the count by loops until t becomes 500 m sec or more. Then, the SVM value is averaged. The average value (SVM_{avg}) of the data from count 0-25 is used. If the SVM_t is not greater than 2G or between 0.95G and 1.05G, it is recognized as "Walking". In the above range, it is recognized as "Falling" if the θ_t value is more than 100° and the range of SVM_{avg} is 0.95G~1.05G, otherwise it is "Running". If the value of θ_t is more than 75°, it is recognized as "Prone Position" if it is more than 40°, it is "Sitting"; if it is less than 40°, it is recognized as "Standing". After recognition at t, it loops to recognize the subsequent data. If count is t or if SVM_{t+1} and SVM_t are equal then end.

RESULTS AND DISCUSSION

Table 2 shows the result of recognizing the behavior using SVM value and θ value proposed in this studyw. Each behavior was measured 30 times. In the case of static behavior, the accuracy was 100%. However, dynamic behavior showed an average accuracy of 91.1%. Especially, the accuracy of "Running" was measured as 86.7%. This is because the range, θ is similar to the SVM threshold of "Falling" and "Running". Also, in the case that it changes quickly that is when the static behavior is less than 0.5 sec, it is difficult to recognize correctly because θ changes rapidly.

CONCLUSION

In this study, we use polar angle (θ) in addition to SVM to improve the accuracy of behavior recognition technology. θ can be expressed as a value (0-180°). Therefore, the value of the acceleration sensor which changes according to the location of the smartphone is compensated. In addition, it is possible to recognize static behavior as well as dynamic behavior using θ. In particular, if the dynamic behavior changes to static behavior, it is possible to recognize whether or not a fall occurs based on the range of θ by setting the window to 0.5 sec. However when the behavior changed to < 0.5 sec, it was difficult to recognize the behavior by SVM value and θ. This is because the value of θ also changes rapidly when the behavior changes within a short time.

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