

Safety Helmet Wearing Management System for Construction Workers Using Three-Axis Accelerometer Sensor

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Abstract: In the Korean construction industry, legal and institutional safety management improvements are continually being pursued. However, there was a 4.5% increase in the number of workers' deaths at construction sites in 2017 compared to the previous year. Failure to wear safety helmets seems to be one of the major causes of the increase in accidents, and so it is necessary to develop technology to monitor whether or not safety helmets are being used. However, the approaches employed in existing technical studies on this issue have mainly involved the use of chinstrap sensors and have been limited to the problem of whether or not safety helmets are being worn. Meanwhile, improper wearing, such as when the chinstrap and harness fixing of the safety helmet are not properly tightened, has not been monitored. To remedy this shortcoming, a sensing safety helmet with a three-axis accelerometer sensor attached was developed in this study. Experiments were performed in which the sensing data were classified whether the safety helmet was being worn properly, not worn, or worn improperly during construction workers' activities. The results verified that it is possible to differentiate among wearing status of the proposed safety helmet with a high accuracy of 97.0%.

Keywords: Construction, worker safety, safety helmet, three-axis accelerometer sensor, data mining

1. Introduction

1.1. Research Background and Objectives

Recently, the importance of worker safety in the construction industry has become a prominent issue, and the Ministry of Employment and Labor in Korea has set a goal of reducing deaths due to industrial accidents by half before the end of 2022. Institutional and legal improvements are being pursued, and the need for safety is being emphasized [1].

Despite this progress, the most deaths occurred in construction industry accidents (579 people, 29.6%) among all industrial accidents in 2017; furthermore, the number of deaths has risen, as there was a 4.5% increase in the number of worker deaths compared to the same period in the previous year [2]. An analysis of construction accidents by body part showed that the head (161 people, 41.2%) and multiple body parts (123 people, 31.5%) were the most frequently injured, and among the fatal construction accidents, falls were the most common type (8,699 people, 32.7%) [3].

These results indicate that it is very important to manage the wearing of safety helmets, which can protect the heads of workers, as there is a high possibility that the head will be the body part that first impacts the ground in a fall accident [3,4].

When safety helmets are properly worn, they provide shock absorption, which reduces the force transmitted to the head of the wearer upon object impact to less than 10%, thus enhancing worker safety. Aside from falls, helmets also reduce the danger from accidents involving falling objects, flying objects, impacts, electrical shocks, and so on. Therefore, numerous institutional and technical studies have been conducted on increasing validity and accuracy when determining whether or not safety helmets are being worn properly [5-9].

In terms of technology, the read sensors have been attached to chinstraps in previous studies to detect emergencies based on such information such as whether or not the helmet is being worn and its position. In those studies, it was determined whether or not the helmet was being worn by using sensors attached to chinstraps or additional sensing data such as altitude and position information. For example, chinstrap sensors and altitude sensing data have been used to confirm that the helmet was being worn [7-9].

However, the previous studies in which sensors were attached to chinstraps were limited in that it is difficult to determine whether or not a helmet is being worn when looking at the movements of a worker in a work environment who fastens the chin strap but does not wear the helmet, carries or wears the helmet on his or her body, or performs other similar activities.

The objective of this research was to resolve the shortcomings of previous studies by developing a system using a three-axis accelerometer sensor to identify the activities of workers in the work area of a current construction site based on their movement data and to determine not only whether or not safety helmets are being worn, but also whether they are being worn improperly.

The development of the system included developing a sensing safety helmet using a three-axis accelerometer sensor, a worker smartphone app to transmit the data acquired by the safety helmet, and a web platform for an on-site PC to store the data. It is expected that managing construction workers who do not wear their helmets or wear them improperly will help prevent construction site accidents.

1.2. Research Scope

In this study, the hardware and software necessary to develop a management system for proper wearing of safety helmets based on three-axis accelerometer sensing were established. This work resolves the shortcomings of existing studies in which sensors were employed and the focus was on whether or not the safety helmet was being worn. This research was focused on developing a method of using worker motion data captured by three-axis accelerometer sensing to determine whether safety helmets are being worn improperly at construction sites. The specific steps performed in this study are described as follows:

First, statistical data on Korean construction site safety accidents were analyzed to understand the importance of not wearing safety helmets, and the necessity of developing a system for monitoring the proper wearing of safety helmets was identified. Existing studies on monitoring the proper wearing of safety helmets have been limited to determining when safety helmets are not being worn. As such, it was observed that improper wearing, such as when the chinstrap and harness of the safety helmet are not fastened correctly, have not been monitored adequately in previous studies.

Second, a sensing safety helmet measurement system was developed in which the safety helmet has a three-axis accelerometer sensor that can identify user activities to monitor whether the safety helmet is properly worn, not worn, or improperly worn.

Third, the raw data from the three-axis accelerometer sensor of the safety helmet were converted into a signal vector magnitude (SVM). The recognition rate for each activity was found to be high, but it was difficult to distinguish between proper and improper wearing.

Fourth, to resolve this problem, the SVM was converted into a frequency by performing a fast Fourier transform (FFT), and specific features were found at certain frequencies. These frequency features were used to classify the data by work activity and to analyze them.

Fifth, the Waikato Environment for Knowledge Analysis (WEKA) data mining program was used to verify that it is

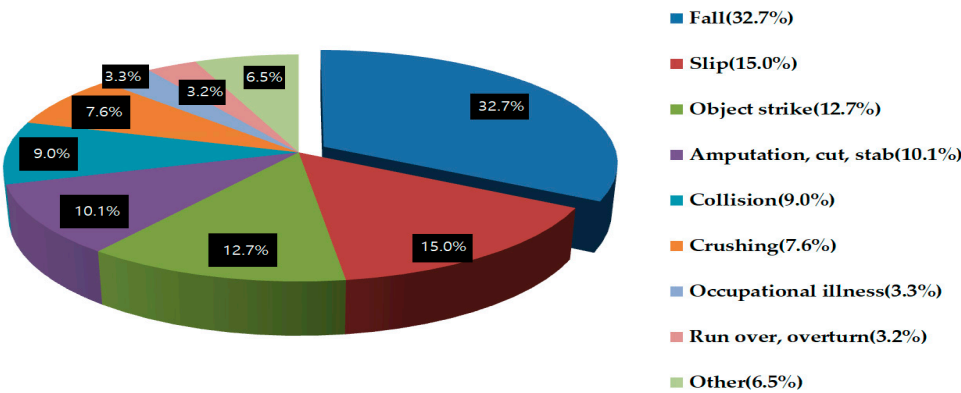
possible to differentiate among proper wearing, not wearing, and improper wearing of the safety helmet during work for each of the work activities.

2. Materials and Methods

2.1. Existing Research Trends

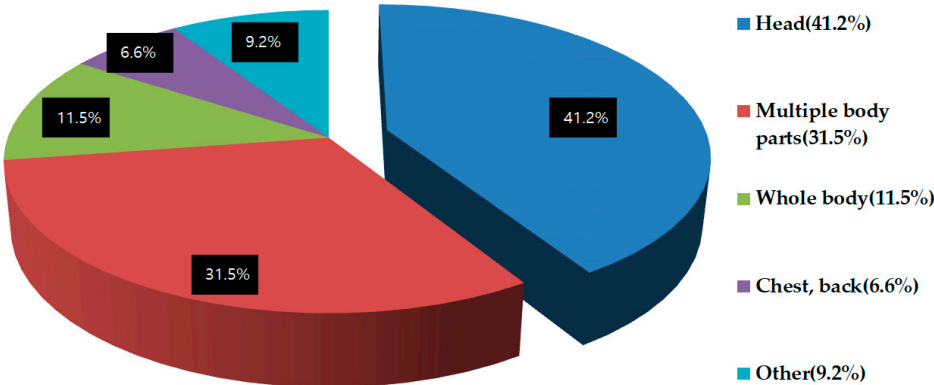
2.1.1. Korean Construction Site Accident Types

[Fig. 1] shows the industrial accidents in 2016 by cause of accident according to the Korea Occupational Safety and Health Agency. Out of the total of 90,656 people involved in industrial accidents, 26,570 (or 29.3%) were in construction accidents. Of those, falls (8,699 people, 32.7%) were the most numerous, followed by slips (3,995 people, 15.0%) and being struck with objects (3,368 people, 12.7%) [3].



[Fig. 1]. Distribution of industrial accidents in the construction industry in Korea by cause of accident

[Fig. 2] shows the industrial accidents by the injured body part. Out of the total of 826 people with body parts injured in industrial accidents, 391 of them (47.3%) were in the construction industry. Among those, the head (161 people, 41.2%) was the most frequently injured, followed by multiple body parts (123 people, 31.5%) [3].



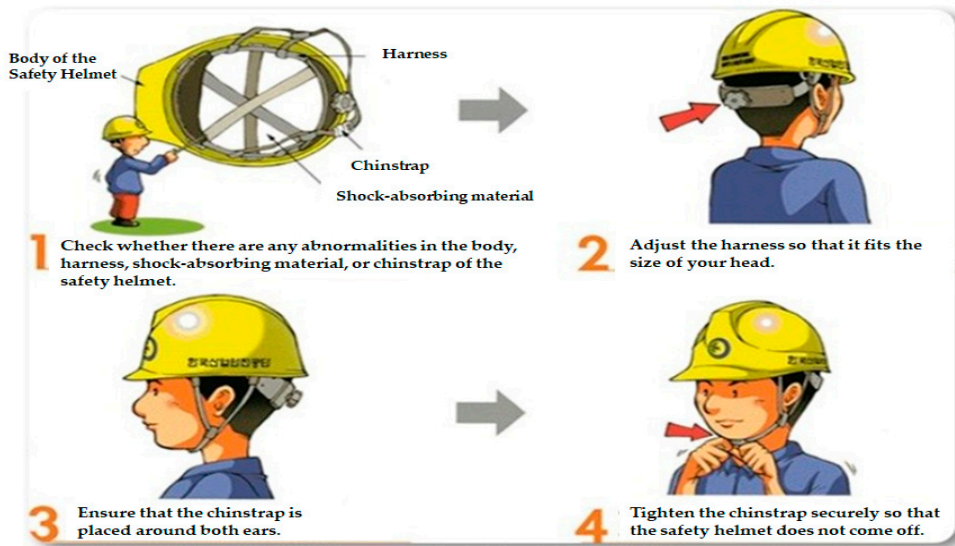
[Fig. 2]. Distribution of accidents in the construction industry in Korea by injured body part

As shown in [Fig. 1], falls often occur at constructions sites (8,699 people, 32.7%). In [Fig. 2], injuries to the head (161 people, 41.2%) account for a high proportion of the injuries by body part. Based on this information, it can be expected that there is a high possibility that the head will impact the ground first during a fall accident. Because the head is the most

108 vulnerable body part, wearing a safety helmet to protect the head is very important. Thus, ensuring head protection is
109 directly connected to promoting worker safety not only in falls, but also in many other types of safety accidents that occur
110 on construction sites, such as those involving dropped and flying objects [3-6].

111 2.1.2. Trends in Research on Improving Safety Helmet Wearing

112 Korean regulations related to industrial safety and health standards stipulate that safety helmets must be worn for
113 protection when doing work that involves a risk of flying or falling objects or the worker falling. Because safety helmets
114 reduce the risk of accidents related to falling objects, flying objects, impacts, and electrical shocks, safety helmets are among
115 the important pieces of protection equipment responsible for worker safety at construction sites [5].



116
117 [Fig. 3]. Occupational safety and health agency guide to wearing a safety helmet

118
119 As shown in [Fig. 3], the Occupational Safety and Health Agency recommends a method of properly wearing a safety
120 helmet that includes checking the helmet for abnormalities, adjusting the harness so that the helmet is the right size for the
121 head of the wearer, and ensuring that the chinstrap is placed around both ears and fastening it securely so that the helmet
122 does not come off [6].

123 Properly wearing a safety helmet in this manner provides shock absorption, which reduces the force transmitted to the
124 head of the wearer upon object impact to less than 10%. However, there are many cases in which workers avoid wearing
125 safety helmets or do not fasten their chinstraps, and safety accidents often occur as a result. To resolve this issue, a case study
126 was conducted involving a system with a sensor attached to the chinstrap that turned on when the chinstrap was fastened
127 and determined whether or not the safety helmet was worn properly [7]. Aside from chinstrap detection sensors, a safety
128 control server was investigated that can determine worker locations through relays by calculating the communication
129 distance based on the communication range to provide notifications about worker locations and emergencies via wireless
130 EMC(Electromagnetic compatibility) [8]. In another study, Zigbee communications and chinstrap sensor, intensity of
131 illumination, and altitude data were used to determine whether or not workers were properly wearing helmets with their
132 chinstraps fastened. This method was employed to determine the locations, emergency situations, etc. of workers [9].

133 However, if a worker does not wear his or her safety helmet and instead places it at the construction site with the chinstrap
134 fastened, the monitoring system may consider the helmet to be worn based on the node status. Even when the
135 determination is made using data such as the illumination and altitude of the worker, if he or she carries the safety helmet
136 without wearing it and creates movement data by performing activities involving motion in the work environment, or if the

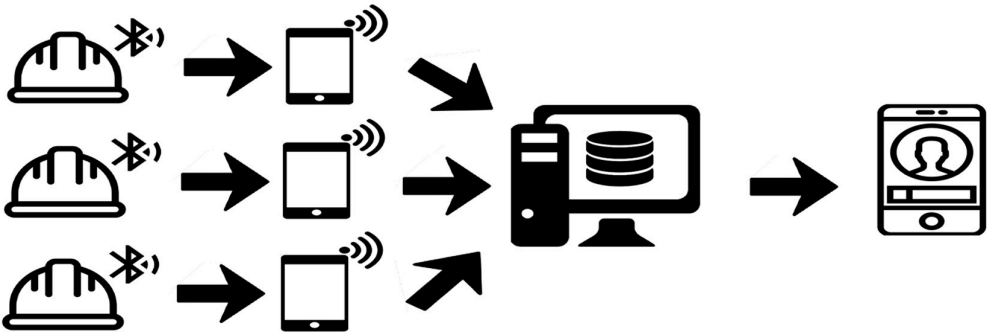
137 worker fastens the chinstrap and keeps the safety helmet on his or her head and moves, it will be determined that the safety
138 helmet is being worn properly and work is being performed at the work location. Thus, it is possible for the system to
139 recognize that the safety helmet is being worn properly even when it is not.

140 To resolve this issue, it is necessary to develop ideas and technology that can determine whether a worker is wearing his or
141 her safety helmet properly while working by using data related to the activities of the worker rather than simply attaching a
142 sensor to the chinstrap of the helmet to determine whether or not it is being worn properly.

143 2.2. Development of Three-Axis Accelerometer Sensing System for Safety Helmet Wearing Management

144 2.2.1. Platform for Saving and Analyzing Sensing Data

145 As shown in [Fig. 4], the proposed system consists of a three-axis accelerometer sensor module
146 attached to the safety helmet, a smartphone app for the worker wearing the helmet, and an on-site
147 PC-based database platform that stores the data



148
149 [Fig. 4]. Data transmission in the three-axis accelerometer safety helmet sensing system

150 The data collected by the three-axis accelerometer sensor attached to the safety helmet are first transmitted to the
151 smartphone of the worker who is wearing the helmet. The data are stored in the developed smartphone app, and
152 Bluetooth is used for communication.

153 These data are then sent to the on-site PC-based database platform via 3G/LTE and uploaded as shown in [Fig. 5],
154 where the X, Y, and Z outputs of the three-axis accelerometer sensor are listed sequentially, and the data collection times
155 and dates are entered.

156 The worker data are transmitted to the on-site PC-based database platform and analyzed in real time. If the helmet is not
157 being worn or is being worn improperly, a warning is sent to the smartphone app of a designated site manager, such as a
158 task leader.

http://hongik.sch.ac.kr/smarthelmet/				
Smart Helmet				
엑셀 저장		데이터 초기화		
no	Acc x	Acc y	Acc z	InsertDay
1	-205	-146	-20	18.8.21 13:41:9
2	-198	-159	-28	18.8.21 13:41:9
3	-200	-157	-30	18.8.21 13:41:9
4	-251	-183	-5	18.8.21 13:41:10
5	-154	-180	-51	18.8.21 13:41:10
6	-208	-166	-1	18.8.21 13:41:10
7	-210	-128	-48	18.8.21 13:41:10
8	-222	-138	-35	18.8.21 13:41:11
9	-238	-148	-2	18.8.21 13:41:11
10	-212	-149	11	18.8.21 13:41:11

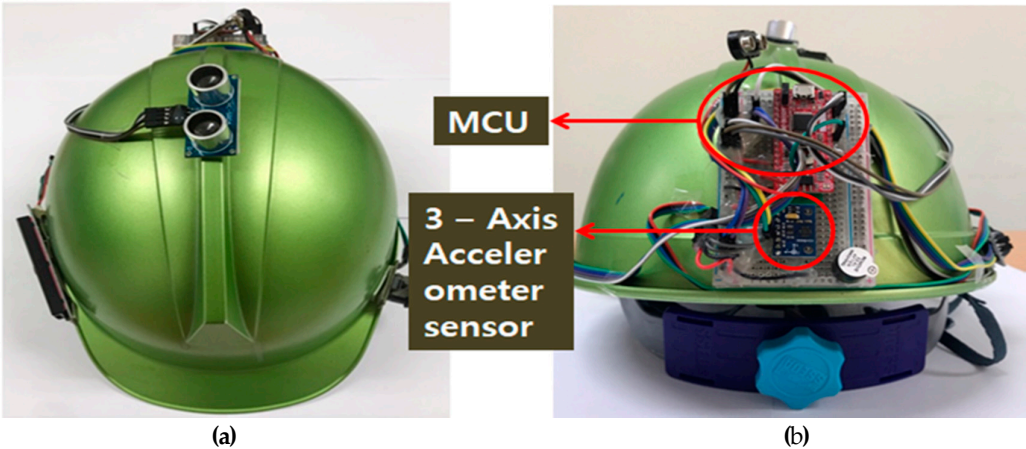
159
160 [Fig. 5]. On-site PC web platform for storing data

2.2.2. Three-Axis Accelerometer Safety Helmet Sensing System Hardware

The safety helmet sensor module developed in this study includes a BLE(Bluetooth Low Energy) feature for communication with smartphones, a three-axis accelerometer sensor, and a real-time clock (RTC) time-measuring sensor and is battery-operated.

A JARDUINO-UNO_BTmini is used in the MCU(Micro Controller Unit) due to its small size. It transmits the three-axis accelerometer and RTC data through Arduino I2C communication with each sensor. The data are transmitted via Bluetooth to the app on the personal smartphone of the worker that is used for data transmission. The three-axis accelerometer sensor uses MMA8452, and the RTC uses DS3231.

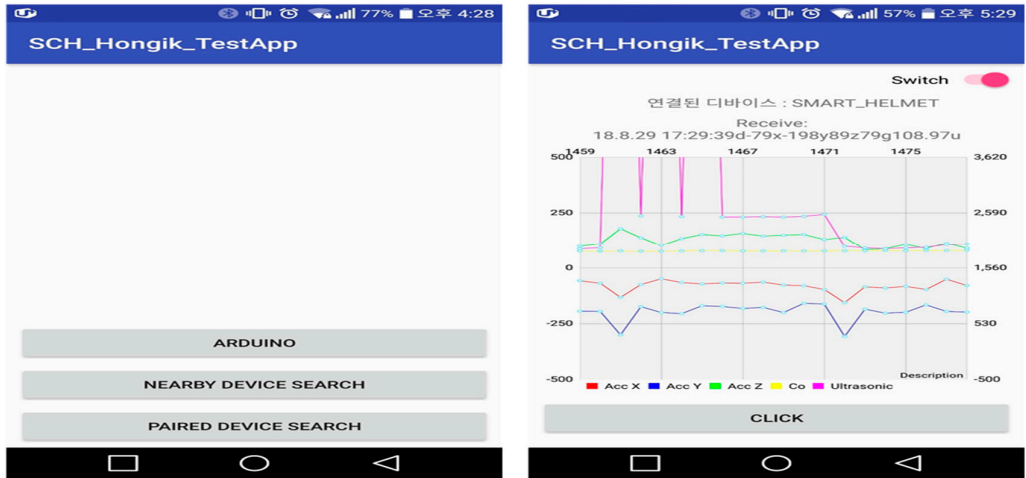
[Fig. 6] shows the three-axis accelerometer sensing helmet employed in the tests in this study. The sensor module is attached to an ABE-type safety helmet, which is the type that is typically used on construction sites.



[Fig. 6]. Prototype of three-axis accelerometer sensing safety helmet : (a) Front side of the Safety Helmet;
(b) Back side of the Safety Helmet

2.2.3. Mobile App for Data Collection and Transmission

[Fig. 7] shows screenshots of the data transmission app for the sensing safety helmet, which can be used on an Android mobile device. The app is designed so that when the mobile device is connected to the sensing safety helmet via Bluetooth, the data from the three-axis accelerometer sensor are automatically stored in the app database. If the data transmission tab is selected in the app, the data that were first saved in the app are sent to the web page of the on-site PC via 3G/LTE. As shown in [Fig. 7], the X, Y, and Z vector values generated by the three-axis accelerometer sensor according to the real-time movements of the worker can be viewed in the app.



[Fig. 7]. Screenshots of the personal smartphone app for transmitting data

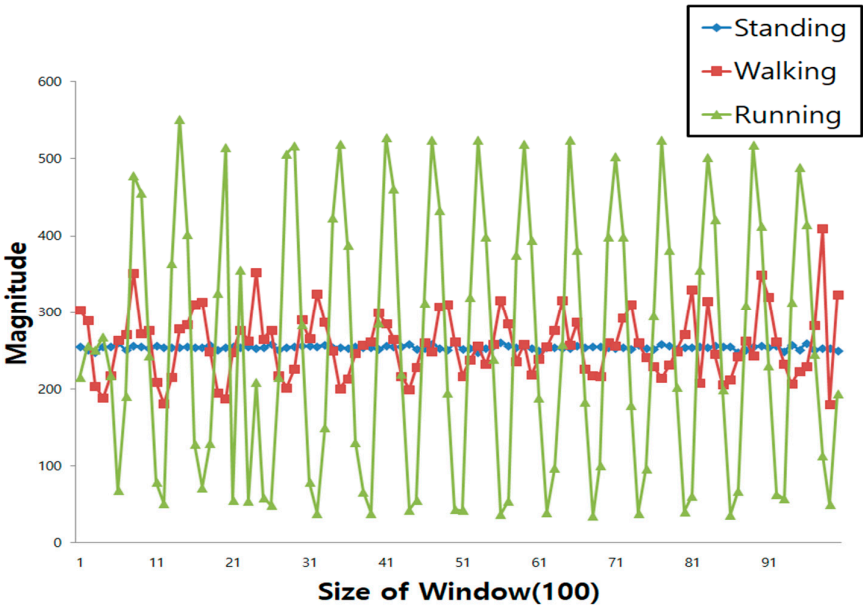
3. Results

3.1. 1st Data(SVM) Analysis

The common method of recognizing activities using a three-axis accelerometer sensor involves converting the signal values by applying Eq. (1) or a statistical formula or using a mathematical algorithm for activity classification [10,11]. Eq. (1) can be applied to determine the SVM, by extracting a single representative value from the X, Y, and Z accelerations output by the three-axis accelerometer sensor. This quantity can be used to offset the directional component of the acceleration along each axis that is caused by gravity and to collect fixed pattern information [12].

$$SVM = \sqrt{a_x^2 + a_y^2 + a_z^2} \tag{1}$$

[Fig. 8] depicts results obtained by applying Eq. (1) to the X, Y, and Z acceleration outputs corresponding to standing, walking, and running when the safety helmet is worn properly with the chinstrap fastened.



[Fig. 8]. SVM during standing, walking, and running when the safety helmet is worn properly

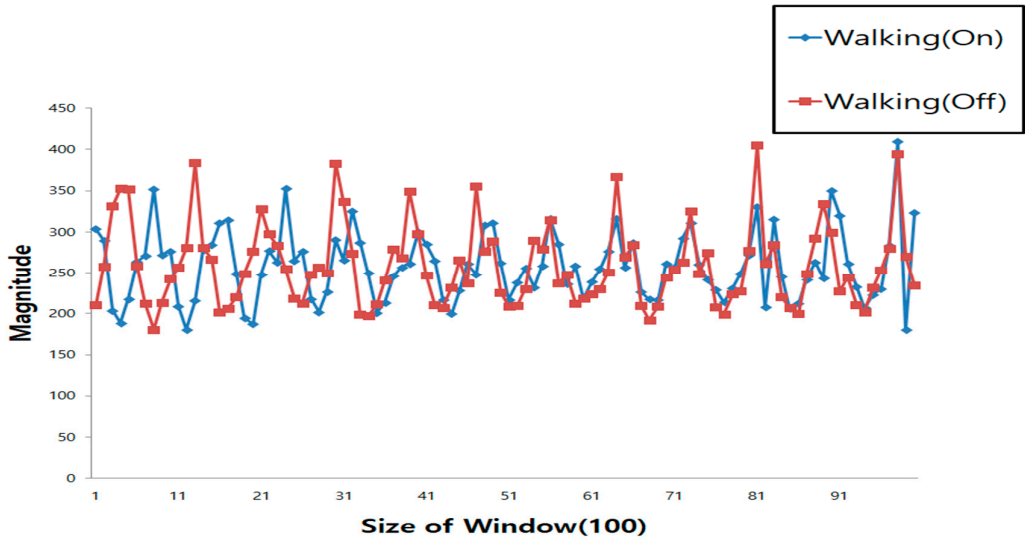
The horizontal axis in [Fig. 8] is the number of data items listed sequentially, and 100 data items were diagrammed. The vertical axis is an index that shows the SVM. Standing, walking, and running, which are typical activities in activity recognition, clearly exhibit a variety of differences following the application of Eq. (1) [13]. Among the three activities, running, which involves relatively large body movements, has the largest SVM. Standing, which entails relatively little body movement, has the smallest SVM.

[Table 1]. Accuracy of SVMs for standing, walking, and running according to whether or not the safety helmet is worn properly

	Standing (On)	Standing (Off)	Walking (On)	Walking (Off)	Running (On)	Running (Off)	Accuracy (%)
Standing (On)	47	39	6	6	2	0	47

Standing (Off)	43	44	5	5	1	2	44
Walking (On)	5	5	34	37	15	4	34
Walking (Off)	6	6	35	36	11	6	36
Running (On)	2	0	14	11	41	32	41
Running (Off)	0	1	5	9	33	52	52
Average							42.3

204
205 Although the data were classified well by activity, there was some uncertainty regarding whether the helmet was worn
206 properly with the chinstrap fastened or worn improperly with the chinstrap incorrectly fastened during each activity, as
207 shown in [Table 1]. [Table 1] summarizes the results of tests performed by dividing the three activities in [Fig. 8] into states
208 with the chinstrap fastened (On) and not properly fastened (Off) and then using the RandomTree algorithm of WEKA to
209 classify 100 data samples. RandomTree is a typical decision-making tree data mining algorithm and forms the basis of
210 RandomForest.
211 [Table 1] shows that the mean accuracy of the decision regarding whether or not the safety helmet is being worn
212 properly during standing, walking, and running is 42.3%. The activity classification accuracy is high, but the accuracy of the
213 classification regarding whether or not the safety helmet was worn properly during each activity is not as high. As an
214 example, [Fig. 9] shows the walking activity, for which the determination of whether or not the safety helmet was worn
215 properly has a particularly low accuracy among the activities in [Table 1].



216
217 [Fig. 9]. SVM during walking according to whether or not the chinstrap on the safety helmet was fastened
218

219 As shown in [Fig. 9], the SVM of the walking activity when the safety helmet was worn properly is larger than when the
220 safety helmet was not worn properly. However, it is considered to be difficult to categorize the walking activity data
221 according to whether the safety helmet was properly worn or improperly simply through visual analysis. As such, an F-test
222 was performed (at a significance level of 0.1) using the variance of the data, resulting in [Table 2] below.

223
224

[Table 2]. F-test results for SVM during walking according to whether or not the chinstrap on the safety helmet was fastened

	Walking (On)	Walking (Off)
Average variation	257.8603916	258.8952746
Dispersion	1865.857006	2511.794754
Observed number	100	100
Degrees of freedom	99	99
F proportion	0.742838165	
P(F ≤ f) one-sided test	0.070441726	
F-rejection value one-sided test	0.772123362	
Result	F-rejection value > F proportion	

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In the F-test results in [Table 2] for the walking activity when the safety helmet was worn properly or improperly, the F-rejection value is greater than the F proportion. Therefore, the data could be classified based on whether or not the chinstrap was fastened. However, the data mining results in [Table 1] exhibit markedly low accuracy. The three-axis accelerometer sensor is sensitive and therefore has physical error, and the data obtained when the safety helmet was and was not worn properly during each activity yielded different F-test results. Nevertheless, the data from the two cases were recognized as the same area and could not be represented correctly [14].

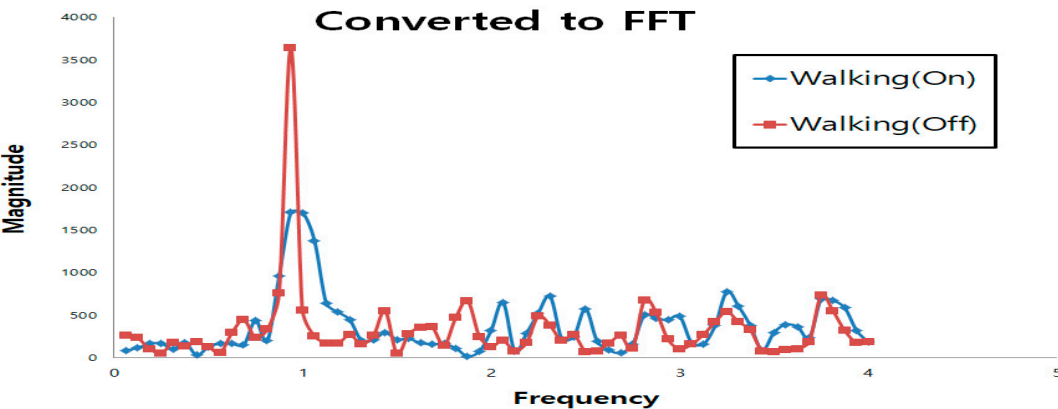
232 3.2. 2nd Data(FFT) Analysis

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To resolve this issue, the SVMs were converted into frequency bands via FFT to classify the data obtained when the safety helmet was worn properly, not worn, and worn improperly. An FFT involves the same formula as a discrete Fourier transformation, but the data size is made 2^n to improve the calculation speed [15]. When an FFT is used in analysis, the sizes of the frequency bands for each activity are distributed differently. Therefore, the proper wearing, improper wearing, and not wearing data for each activity can be identified [16].

239
238

$$\begin{aligned} X_k &= \sum_{n=0}^{N-1} x_n e^{-\frac{2\pi i}{N} kn} \quad (k = 0, \dots, N-1) \\ &= \sum_{n=0}^{N-1} x_n \left(\cos\left(\frac{2\pi kn}{N}\right) + j \sin\left(\frac{2\pi kn}{N}\right) \right) \quad (2) \end{aligned}$$



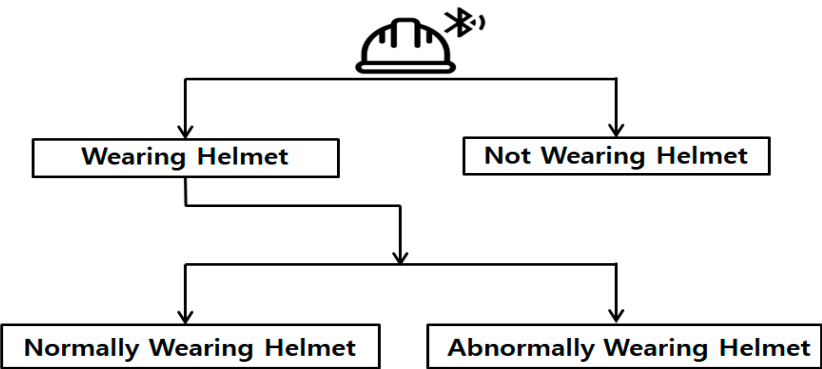
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[Fig. 10]. Results of FFT conversion of walking activity according to whether or not the safety helmet was worn properly

[Fig. 10] shows the results of using Eq. (2) on the data in [Fig. 9] and conversion via FFT. To perform an FFT, 2ⁿ data are needed, so the walking activity data were separated into On and Off states, and the number of data was set to be the same at 64. In [Fig. 10], there is a pattern in which both the On and Off states of the walking activity are prominent in the 0.85–1 Hz range. Near 1 Hz, the slope of the graph changes gradually for the On data but changes rapidly for the Off data.

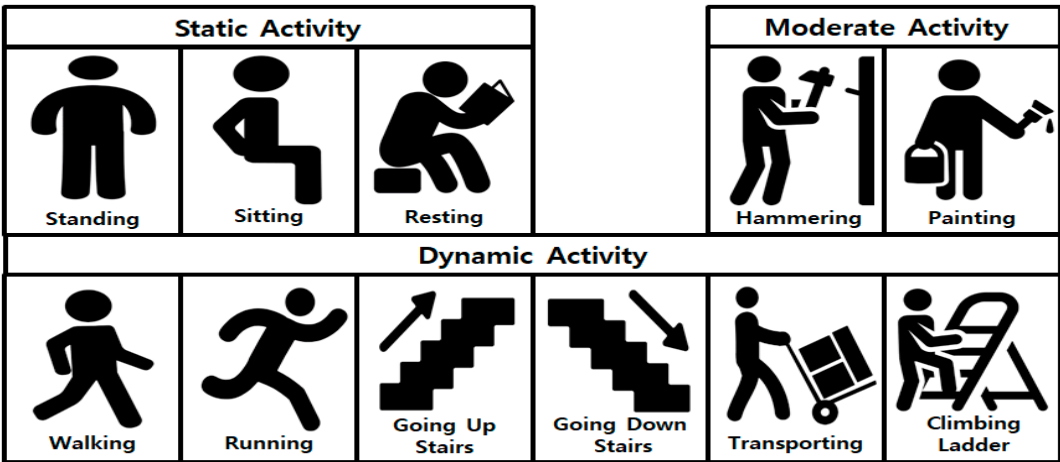
3.3 Test Scenario for using FFT Data

The focus of this study was the proper wearing of safety helmets at construction sites. To distinguish between wearing and not wearing a helmet and then between properly and improperly wearing the helmet, the test scenario depicted in [Fig. 11] was created.



[Fig. 11]. Safety helmet state classification chart

First, a determination is made regarding whether or not the safety helmet is being worn. If the helmet is being worn, it is determined whether the helmet is being worn properly or improperly. For this purpose, it is necessary to classify the worker activities. In existing studies on sensor-based activity recognition, activities such as walking, standing, running, riding a bicycle, going up stairs, and going down stairs have been classified [17-20]. Since the focus of this study was on worker activities at a construction site, the test scenarios were classified accordingly, as shown in [Fig. 12].



[Fig. 12]. Classification of static, moderate, and dynamic activities of workers in test scenarios

In this study, 11 typical main activities of workers at a construction site were identified and were divided into static, moderate, and dynamic activities. The static activities include sitting, standing, and resting and generally involve minimal upper and lower body movements. Resting allows the upper body to move more freely than sitting. The moderate activities include hammering and painting. Here, the lower body is generally static, but the upper body is moving to perform a task. Finally, the dynamic activities include walking, running, going up stairs, going down stairs, transporting objects, and climbing ladders.

The data sampling period of the sensor was 8 Hz, and a data frame was created to allow data sampling to occur 128 times every 32 s. Every 128 data items constituted a set, and 100 sets of raw data were collected regarding the proper and improper wearing of safety helmets according to activity. The tests were performed on three men and two women to consider a variety of body conditions. Each subject performed each activity for 2–30 min, depending on whether the chinstrap was fastened or not. When the safety helmet was properly worn (On), the harness was adequately tightened around the head, and the chinstrap was 2 cm vertically from the tip of the chin of the subject. When the safety helmet was improperly worn (Off), the harness was loose, and the chinstrap was not properly fastened.

3.4 Final Test Analysis Results

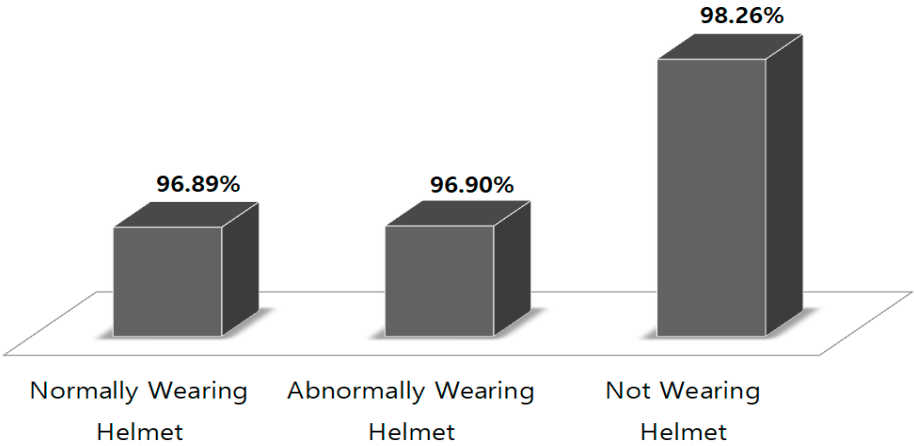
[Table 3] below shows the results of applying the RandomTree algorithm from WEKA to the proper wearing (On), improper wearing (Off), and non-wearing of the safety helmet proposed in this study according to the activities of the workers. The accuracy is the highest when using the RandomTree algorithm.

As shown in [Table 3], the data derived from each activity have a high recognition rate. The good activity recognition indicates high classification performance, i.e., several activities can be classified, and the data can be categorized according to whether or not the safety helmet was worn during each activity. When the safety helmet was not worn, in which case the highest accuracy was found, 12,577 data out of a total of 12,800 data were accurately recognized as having been obtained when the helmet was not worn, yielding the best data verification performance (98.26%).

[Table 3]. Experimental classification results for properly wearing, improperly wearing, and not wearing the safety helmet according to worker activity

			Predicted Class (Cross-validation Folds 30)																									
			Sitting		Standing		Resting		Hammering		Painting		Walking		Running		Going up Stairs		Going Down Stairs		Transporting		Climbing Ladder		Not Wearing Helmet		Accuracy (%)	
on	off	on	off	on	off	on	off	on	off	on	off	on	off	on	off	on	off	on	off	on	off	on	off	on	off			
Actuator 1	Sitting	on	12389	41	33	50	49	46	25	20	27	34	6	12	0	5	10	8	3	0	12	6	4	4	16	96.79		
		off	34	12388	72	32	72	41	14	13	31	25	2	3	0	1	6	4	2	2	2	0	1	4	51	96.78		
	Standing	on	42	52	12380	38	62	48	24	15	36	34	0	2	0	2	2	2	5	1	0	0	2	2	51	96.72		
		off	25	44	48	12423	54	62	18	18	25	20	6	2	2	6	3	2	0	0	0	14	2	2	24	96.79		
	Resting	on	28	54	68	69	12389	43	14	8	34	24	2	2	0	4	0	7	1	0	4	6	0	6	37	96.79		
		off	44	46	34	54	43	12396	23	20	50	30	5	6	4	0	2	4	0	5	2	2	10	2	18	96.84		
Cylinder	Hammering	on	19	8	22	8	2	36	12448	32	26	43	26	18	9	2	16	8	4	8	16	26	6	15	2	97.25		
		off	23	14	21	14	21	12	35	12430	18	20	22	18	11	10	25	12	10	16	6	26	12	22	2	97.11		

a s s	Painting	on	35	17	29	34	38	27	30	23	12412	38	15	16	8	7	6	6	6	4	16	14	10	4	5	96.97	
		off	32	32	26	32	19	39	26	28	46	12392	14	25	0	0	14	11	0	8	20	16	10	4	6	96.81	
	Walking	on	10	6	2	2	4	1	20	16	15	12	12444	25	30	25	18	13	30	23	20	22	22	40	0	97.22	
		off	9	0	2	6	4	6	15	16	7	4	40	12419	25	34	19	20	34	8	40	29	26	37	0	97.02	
	Running	on	2	0	0	0	2	2	9	9	4	4	30	13	12413	37	41	48	41	34	26	23	38	24	0	96.98	
		off	7	0	0	2	2	0	4	11	3	2	26	22	52	12414	22	40	40	40	24	20	44	25	0	96.47	
	Going up Stairs	on	6	6	2	12	0	7	20	16	14	5	30	38	34	38	12348	38	18	28	34	36	40	30	0	96.47	
		off	0	4	7	6	0	4	6	6	8	9	32	28	36	33	34	12388	26	32	35	16	36	54	0	96.78	
	Going Down Stairs	on	2	0	0	2	4	2	4	18	6	4	30	38	50	34	40	40	12370	32	36	18	34	36	0	96.64	
		off	5	0	0	2	4	1	10	12	8	6	34	28	37	29	31	22	25	12423	22	32	30	37	2	97.05	
	Transporting	on	4	2	4	4	2	3	22	30	10	14	47	36	28	20	22	12	20	34	12416	30	20	20	0	97.0	
		off	0	4	2	2	2	6	16	22	10	4	35	24	41	30	22	22	24	18	44	12397	34	40	1	96.85	
	Climbing Ladder	on	3	2	6	2	4	1	16	6	4	6	29	32	38	28	26	48	42	34	18	32	12405	16	1	96.92	
		off	11	4	2	4	4	2	13	20	6	6	28	32	24	30	28	38	41	34	27	20	20	12406	0	96.92	
	Not Wearing Helmet			22	50	47	37	36	17	2	0	6	2	0	2	0	0	1	1	0	0	0	0	0	0	12577	98.26
			Average																								96.95



[Fig. 13]. Results of analysis of the recognition accuracy for properly wearing, not wearing, and improperly wearing the safety helmet for each worker activity

[Fig. 13] shows the accuracy verification results for properly wearing, improperly wearing, and not wearing the proposed safety helmet, based on the data in [Table 3]. The mean recognition rates for the 11 considered typical worker activities at construction sites are 96.89% for properly wearing the safety helmet and 98.26% for not wearing the helmet,

296 which indicate good classification performance. A high accuracy of 96.90% was also achieved for the data obtained when
297 improperly wearing the helmet.

298 **4. Discussion**

299 In this study, three-axis accelerometer sensors that can classify human activities were attached to safety helmets and
300 sensing data were collected and analyzed to determine whether or not safety helmets were being worn properly during
301 work. In previous studies in which three-axis accelerometer sensors were used to recognize activities, the sensors were
302 attached to smartphones, wearable devices, body parts, etc. and the data were analyzed [21-26].

303 In the existing studies on user activity recognition via three-axis accelerometer sensors, the determinations were made
304 using only the size of the data of the three-axis accelerometer sensor; however, it is necessary to classify data by using several
305 statistical methods regarding the sizes of the vertical and horizontal components and the directionality of the smartphone
306 [21].

307 However, when activities cannot be accurately identified using only the size of the data of the three-axis accelerometer
308 sensor, the FFT can be used to differentiate clearly between static activities for which the data are confusing such as “sit” and
309 “stand” [22]. The data acquired in dynamic environments such as vehicles were simultaneously combined with the activity
310 data as they were obtained. The chaotic data with overlapping pattern ranges were reanalyzed by performing an FFT, and
311 the common patterns of specific unique frequencies were used as features to classify activities posture [12]. FFT analysis, in
312 which points in time with sudden irregular patterns are recognized as state changes, is seen as a very suitable method for
313 analyzing three-axis accelerometer sensor data [23].

314 In this study, a safety helmet with a three-axis accelerometer sensor attached was developed for worker activity analysis. In
315 the proposed method, data obtained when the helmet is worn properly with the chinstrap correctly fastened, worn
316 improperly with the chinstrap not correctly fastened, and not worn are employed to differentiate among properly wearing,
317 improperly wearing, and not wearing the helmet.

318 **5. Conclusions**

319 Most existing technological approaches for promoting the proper wearing of safety helmets involve attaching a sensor
320 to the chinstrap of the helmet to determine whether or not it is being worn properly using data pertaining to whether or
321 not the chinstrap is fastened, as well as additional sensing data. However, it is not possible to determine whether a safety
322 helmet is being worn improperly solely by using a sensor attached to the chinstrap.

323 To resolve this problem, a system in which a three-axis accelerometer sensor is attached to the safety helmet was
324 developed in this study. This system can be used to identify not only when the helmet is being properly worn or not
325 worn, but also when it is improperly worn by employing the sensing data generated during work according to the
326 activity of the worker at the construction site. The developed system was verified by performing tests using the
327 RandomTree algorithm from WEKA. The results confirmed that the system can classify when a safety helmet is being
328 worn properly, being worn improperly, and not being worn with mean accuracies of 96.89%, 96.90%, and 98.26%,
329 respectively.

330 This study is expected to contribute to the prevention of construction accidents by monitoring whether or not
331 construction workers properly wear safety helmets. It is also expected to serve as a first step toward identifying worker
332 activities and whether or not work is occurring by using three-axis accelerometer sensing.

333 Because a high recognition rate can be achieved when classifying worker activities using a three-axis accelerometer
334 sensor, it is believed that the applications of this method will be expanded in the future through studies on construction
335 work process improvement and productivity management.

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