A Smart Safety Helmet using IMU and EEG sensors for analysis of worker's fatigue

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***Abstract*—It is known that head gesture and mental states can reflect some human behaviors related to a risk of accident when using machine-tools. The research works presented in this paper aim to reduce the number of injury and thus increase worker safety. Instead using camera, this paper presents a Smart Safety Helmet (SSH) in order to track head gestures and mental states of worker able to recognize anomalous behavior. Information extracted from SSH is used for computing risk level of accident (a safety level) for preventing and reducing injury or accidents. The SSH system is an inexpensive, non-intrusive, non-invasive, and non-vision-based system, which consists of 9DOF Inertial Measurement Unit (IMU) and dry EEG electrodes. A haptic device, such as vibrotactile motor, is integrated to the helmet in order to alert the operator when computed risk level (fatigue, high stress or error) reach a threshold. Once the risk level of accident breaks the threshold, a signal will be sent wirelessly to stop the relevant machine tool or process.**

Key words* — *Safety; Head motion recognition; IMU; EEG; accident avoidance; human machine interaction

I. Introduction

Some mental states, such as fatigue, stress or sleepiness are known to increase potential accident in industrial facility, therefore, could decrease productivity, and increase the cost of healthcare if the potential accident comes true. The highest rate of industrial incidents is usually found among shift workers due to fatigue or extended work hours [1]. Fatigue levels are not easily quantified, therefore it is difficult to identify the effect of fatigue on accident and injury rates. However, fatigue is still considered a contributing factor with 20% of confidently in reported accidents and incidents across all sectors [2]. When using machine tool, the risk of injury increases due to disturbance, lack of concentration, vigilance decline, and neglect of the risk during prolonged use.

The guiding objective of this research project is to develop a device able to recognize abnormal behaviors of workers which endanger whose safety and health. This paper proposes an inexpensive, non-intrusive and non-invasive Smart Safety Helmet (SSH) system, which is non-vision-based system. The SSH includes mechanic components, electronic hardware for sensing human behaviors, an embedded real-time artificial intelligence module, a wireless transmission to communicate with the tool, and an electronic medical records (EMR). Fig. 1 shows a first design of Smart Safety Helmet (SSH).

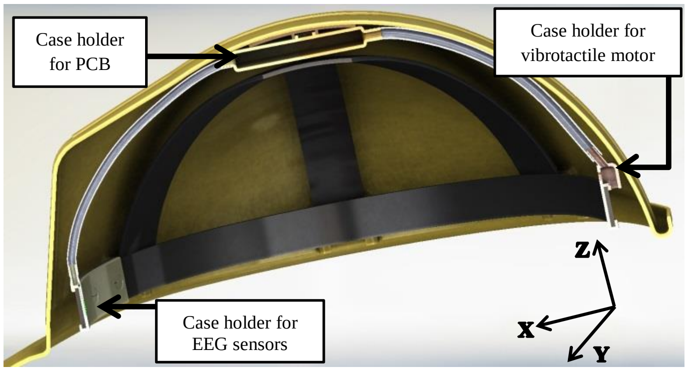

Figure 1.Sectional drawing of the Helmet

This innovative product aims at evaluating anomalous behaviors and user's habits inside different workplaces. The data coming from the SSH could be saved in an electronic medical record and then be used in order to increase safety or even productivity via diagnostic aid software and real-time biofeedback. Using an artificial intelligence algorithm, it could identify the risk level coming from health issues such as bad posture, potential risk when using a rotating tool, fatigue, sleepiness, high stress, etc. As an essential step, the risk level evaluation with electroencephalography (EEG) and Inertial Measurement Unit (IMU) is presented in this paper.

II. Related Work

In contrast of video-based monitoring devices, wearable EEG and Inertial Measurement Unit (IMU) sensors are chosen for risk level analysis, since they are lighter, low cost and could be integrated to any safety clothing. This section explains the review of IMU and EEG technology and then presents the contribution of this paper.

A. Inertial Measurement Unit (IMU)

Essentially, any human motion could be divided to a series of displacements accelerated by the muscle of torso or limbs. IMU sensor is a device able to measure the moving object's acceleration, velocity, orientation, using a combination of accelerometers, gyroscopes and magnetometers. Consequently, the body-mounted IMU is able to measure the body parts movement. With the development of semiconductor, miniature IMU with low cost and power consumption, are widely applied in motion measurement and tracking [3, 4], gait analysis [5, 6], inertial navigation and positioning [7-10] as a wearable solution, and even in robotic system using artificial intelligence [11] as an embedded component.

IMU sensors are also used in human gesture recognition. For example, Liu et al. present uWave algorithm focusing on personalized and user-dependent hand gesture recognition [12]. A single 3DOF accelerometer is used to measure hand movements according to a vocabulary including eight gestures. Classification is completed using dynamic time warping (DTW) algorithm which measures similarities between two time series of accelerometer readings. Another example is found in [13], where Zhou et al. employ an accelerometer for finger gesture recognition. The time-domain analysis and forward selection algorithm of stepwise regression is adopted to evaluate finger gestures in order to get the optimal feature set. Also, a robot-assisted living system for elderly people is introduced in [14], which fuses the data collected by foot- and waist-mounted inertial sensors to recognize the subject's daily activities in order to convey control information automatically to the assisting robot.

In head-mounted display (HMD) field, Foxlin et al presents two commercial IMU sensor systems designed for head tracking applications [15, 16]. Sensor fusion is performed by a complementary Kalman filter to weigh the gyroscopic angular rate and gravimetric tilt by accelerometer. In [17], the authors employ two group of aforementioned system to track head relative motion to a moving vehicle simulator. Similarly, the head-mounted IMU is able to measure the head motions in order to recognize worker's behavior associated to a risk of accident. Risk level evaluation could be found in risk of falling application. Personal risk assessment uses an algorithm for computing signal features in order to identify the correlation between motion related to fall and the risk level [18, 19].

Helmet-mounted IMU sensors in the SSH are exploited to recognize head gesture (yes, no, look up and down) and some activities (walking, turning and climbing) such as the application described in [14] using the DTW algorithm in [12]. The gestures and activities will be classified using patterns in order to determine the human's intention, and then be used for risk level analysis. This risk level could be computed through analyzing parameters of head motion, and then differentiate gestures such as nodding off. In order to improve robustness, gesture recognition is fused with EEG signal, detailed in the next section.

B. Electroencephalography (EEG)

In industrial environment, repeated working activities, noise level, and shift change could affect the worker physiological status, mental states and then possibly result in fatigue, lack of concentration, vigilance decline, and sleepiness. These abnormal physiological statuses are known as potential threats to the human health and factors of accidents and injuries [20]. Mental state represents an important factor for characterizing worker's physiological status. For example, mental state should be related to the stress caused by a finger or hand jammed in a machine. When detecting stress, the machine should be shut down immediately. Consequently, monitoring the mental states of operators could identify potential and current risk, and be helpful to prevent injury and accident.

Previous researches have indicated that information regarding mental states, such as vigilance, sleep, and awake, could be reflected in the EEG record accurately [21, 22]. In practice, monitoring the change of alpha (between 12 Hz to 30 Hz) and beta brainwaves (ranged between 8Hz to 12Hz) could determine if mental state is transiting from alert to non-alert [23] which could increase the potential risk level of accident. For example, Chin-Teng et al. present a real-time wireless EEG-based brain-computer interface (BCI) system using three EEG electrodes for drowsiness detection in vehicle applications. The reported average of precision and sensitivity achieve 76.9% and 88.7%, respectively [24].

Over the past decades, the portable dry EEG electrodes have been developed and applied to detect and analyze human intentions in order to generate commands to control external devices or computer applications [25]. Some wireless EEG-based BCI systems are implemented as application of brain gaming [26] and physiological states detecting [27]. Dry electrodes are implemented in the SSH system, since they make EEG signal acquisition convenient and easy.

C. Contributions

The conventional methods for human protection usually are static and passive, such as the applications in [28, 29], the varying of capacitive electric field is used to detect human presence in the safeguarding area of industrial facility. Instead, the research work in this paper combines active head gesture recognition with EEG monitoring to estimate human state and intention. Then, an algorithm fuses the both signals of head gestures and mental states, rather than only one, to determine the vigilance and stress of human in order to evaluate a risk level of accident. When an anomalous head motion state is detected, real-time assistance, as the first step, can be used to convey non-visual information to the user using haptic biofeedback, such as vibration motor [30, 31]. Furthermore, if a drowsiness or stress signal is detected, the risk level should increase enough in order to shut down the tool and avoid accident.

III. Proposed System

The SSH system contains IMU sensors, EEG systems and vibrotactile actuators, as illustrated in Fig. 1. This section is focusing on the overall system implementation including the electronic device, the embedded software including an intelligent algorithm, and the mechanical structure of the safety helmet. The prototype consists of two parts: hardware presented in section III-A and software in section III-B.

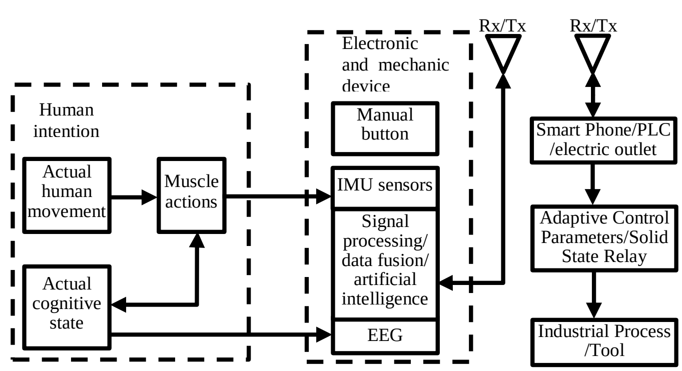

Figure 2. Block diagram of the SSH system

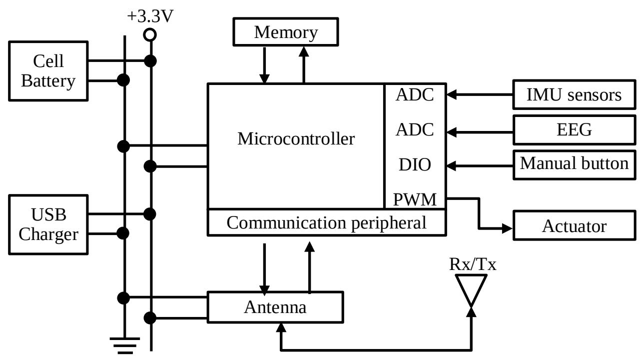

Figure 3. Diagram of electronic board

A. *Hardware*

The SSH system, shown in Fig. 2, is assembled by a safety helmet as a base, an electronic board for real-time signal analysis, wireless transmission capabilities and three dry electrodes for EEG signal acquisition. The IMU sensors are integrated onto the electronic board, which is embedded into the specially designed safety helmet. Fig. 2 illustrates the block diagram of the SSH hardware configuration: human intention measured by the IMU and EEG, wireless transmission and a receiver such as Programmable Logic Controller (PLC) able to control the industrial setup or Solid State Relay (SSR) cutting off the machine tool power supply. Each components are described in the following:

- **Safety Helmet.** The safety helmet is the footing of the system. The electronic board is fixed on the top center of the helmet in order to align the vertical acceleration sensing with the center of gravity, and align the horizontal forward sensing with the sight-line. The three EEG electrodes are fixed on the front inside of the helmet in order to press against the forehead [32, 33]. Fig. 1 shows the coordinate frame definition of the helmet as well as the head. The X-axis indicates forward and backward; the Y-axis indicates the left and right; the Z-axis indicated the up and down of the head.

- **Electronic board.** The electronic board, shown in Fig. 3, is the core unit of the artificial intelligence module of the SSH system, with a printed circuit board dimension of 38 × 28 mm. Primary components on this unit include IMU sensors for posture and gesture sensing, a PIC24 microcontroller from Microchip, a wireless module, a SD card for data record, and a USB connector for data reading and battery charge. Data could be saved into the SD card or be transmitted to Android smart phone via Bluetooth module.

- **EEG.** The EEG are used to acquire brainwaves in order to extract mental states information. Conventional EEG electrodes used in clinic are predominately wet types with Ag/AgCl using adhesive gel interfaces. They are inconvenient to prepare and mount, especially in wearable application. The SilverBumps™ brand dry electrodes from the Orbital Company is specifically designed to be used in wearable application. The dry electrodes eliminate skin preparation and messy gels, which improve experience for users and easy to mount for manufacturing the helmet. The diameter of the electrode is 25 mm, and its resistance is only 0.25 Ω between surface and bottom [34]. The EEG electrodes are connected to the PCB board via an amplifier circuit. Brainwave signals acquired is processed by the PIC24 microcontroller in order to evaluate mental state.

- **IMU sensors.** The IMU sensors include 3-axis accelerometer, 3-axis gyroscope, as well as 3-axis magnetometer. The data mainly used in this paper comes from a digital accelerometer, ADXL345, which has a programmable sensing range up to ±16 g measurement.

B. *Software*

The sensing data coming from both IMU (head motion) of EEG (brainwave) are processed in order to find head gesture and mental state. Therefore, these information are analyzed in order to compute a risk level. The risk level could be associated to any injury with a machine tool or a risk of accident coming from an industrial process. The data analysis in this paper is completed through three software embedded on a microcontroller, an Android device and a PLC. These software are explained in the following:

- **Artificial Intelligence module.** The SSH monitors brainwaves and head motion (gesture and posture) in order to characterize human behavior in the context of a specific workflow within a workspace. Extraction of intelligible information is extracted from raw data using an artificial intelligence algorithm such as those in [12, 13, 32, 35]. Risk level is then computed on the basis of previous experience and surrounding tools or processes. As in the aerospace industry, risk evaluation carried out using real-time algorithms considers three parameters: probability of occurrence, severity of the mishap, and exposure.

- **Electronic Medical Record.** The focus of this system is the development of a technique for the visualization of smart safety helmet data for the purpose of evaluating user performance based on a sequence of mental states and head motions. Combined with a historical database, these performance indicators could shed light on causes of an accident or a drop in productivity. Therefore, risk levels could be mapped to different workplaces in a building and could be managed in function of the specific need.

- **Non-visual biofeedback.** The embodiment also includes means for the system to communicate directly with the user via non-visual biofeedback. It is known that tactile feedback can be exploited in order to present data [36]. In this project, a haptic actuator is exploited in order to allow bidirectional communication with an Intelligent Assistive Device (IAD) through a risk-management algorithm.

IV. METHODOLOGY

The proposed system aims at recognizing the user head gesture and mental states in order to detect the risk level of accident in an industrial facility. To achieve such purpose, it is essential to differentiate the risky head motion and mental state from the safe ones and detect situation while a worker need immediate assistance. This section describes the experiment hypothesis, the strategy for head gesture measurement, and then the risk level logic.

A. *Hypothesis*

As discussed in previous sections, fatigue and sleepiness are considered as a dangerous state for workers in industrial facility. Usually, at the beginning of sleepiness, the head has an involuntary and sudden downward motion, named as “nodding off”, following the rotation in the Y-axis. In the context of this paper, identifying this type of head motion can represent the “fatigue and sleepiness state” of the worker from the view of gesture recognition. Meanwhile, the strength (energy level) of alpha brainwave, which represents non-alert state [23], should increase significantly in EEG signal. The hypothesis is then: risk level of accident could be evaluated as a function of gesture recognition and brainwaves.

B. *Head gesture vocabulary*

The proposed SSH need a database of gestures in order to make a clear differentiation of acceptable motions in a workflow compared to others. Simulating the activities in a real working environment, the head motions could be sorted into two groups of basic actions corresponding to torso stillness and torso moving such as described in Tables 1 and 2.

TABLE 1.THE DICTIONARY OF HEAD MOTION AT TORSO STILLNESS

Motion	Plane	Gesture	Motion	Plane	Gesture
(a). Nodding off			(d).Looking Up		
(b). "Yes" or Pitch			(e). Idle		
(c). "No" or Yaw			(f).Looking Down		

TABLE 2.THE DICTIONARY OF HEAD MOTION AT TORSO MOVING

Motion	Plane	Gesture	Motion	Plane	Gesture
(g). Go Upstairs			(j).Turn Left		
(h).Walk Straight			(k).Stoop down		
(i).Go Downstairs			(l).Turn Right		

To clearly describe the head motions and better understanding the motion frame, a gesture dictionary including 12 basic motions is defined and created. The head motions at torso stillness include: *nodding off* (head falling suddenly and fighting it), *head nod* or Pitch (meaning *yes*), *head shake* or Yaw (meaning *no*), *looking up* (Pitch-up), *looking forward* or neutral position as *idle*, and *looking down* (Pitch-down) as shown in Table 1. The head motions at torso moving include: *go upstairs*, *walk straight*, *go downstairs*, *turn left*, *stoop down*, and *turn right* as shown in Table 2. The two **bold** axes constitute the moving plane of corresponding head motion.

C. *Risk level determination by data fusion*

The mental states extracted from EEG could be sorted to three groups, which are defined as high risk states (fatigue or stress), middle risk states (beginning of fatigue or stress), and low risk states (vigilant), as shown in Fig. 5. The IMU and EEG data are fused in order to calculate the accident severity level shown in Table 3.

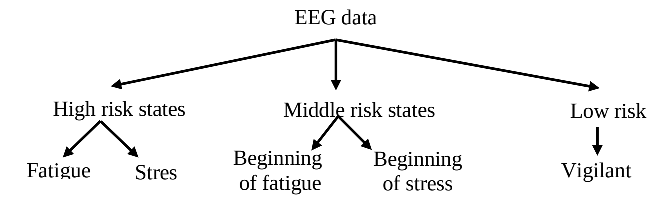

Figure 5. Mental states category by EEG.

Each parameter is given a score from 1 to 3 according to its underlying relationship with severity of the accident or injury. The severity level is determined by the score multiplication of head motion and mental state. Table 3 shows some samples about how to evaluate the severity level. The results are categorized in three class levels: “Low”, “Middle”, and “High” severity level for following risk level computation.

TABLE 3. SEVERITY LEVEL DETERMINATION SAMPLE

	Vigilant (1)	Beginning of Fatigue or Stress (2)	Fatigue/Stress (3)
Torso Moving (1)	Low (1)	Low (2)	Middle (3)
Torso Stillness(2)	Low (2)	Middle (4)	High (6)
Nodding Off (3)	Middle (3)	High (6)	High (9)

Then, the accident risk level is determined by (1).

$$Risk = P * O * S, \quad (1)$$

where, O is the occurrence, S is the severity and P the probability of the accident. When the head gesture is repeated, O value is increased accordingly. S is the severity which is determined from the data fusion of head gesture and mental states defined in Table 3. P is the probability of the accident, computed from the Energy weight of relevant frequency of mental state in the EEG data using Fast Fourier Transform (FFT). Herein, the energy of Alpha [8-12Hz] and Beta [12-30 Hz] is used to indicate alert or non-alert according to (2):

$$Weight_{\alpha} = \frac{\sum_{8}^{12} E_{freq}}{E_{total}}, \qquad Weight_{\beta} = \frac{\sum_{9}^{30} E_{freq}}{E_{total}}, \quad (2)$$

where E_{freq} is the energy inside the sub band frequency for each brainwave parameters (Alpha, Beta, Gemma, etc.) and E_{total} is the total energy of all the frequency spectrum.

V. EXPERIMENTAL RESULTS

According to the *head gesture vocabulary*, 3 male students wore the Smart Safety Helmet to perform these actions in order to acquire the IMU signal of each gesture. A simple explanation of the vocabulary was given to these participants to understand the motions and their sequence. There was no special training on the vocabulary. These measurements are collected at a sampling frequency around 50 Hz which is enough for head motion tracking. Each motion was repeated three times per participant for a total of nine acquisitions per gesture, except *Go upstairs, Walk straight, Go downstairs* and *Idle* where three acquisitions, approximate 2 seconds per gesture, are used in the analysis. In the next section, a one way ANOVA is used for differentiating those gestures.

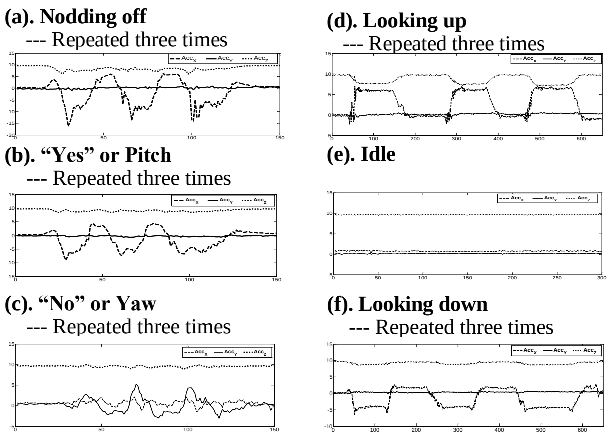

Figure 6. 3-DOF acceleration signals of each head motion at torso stillness

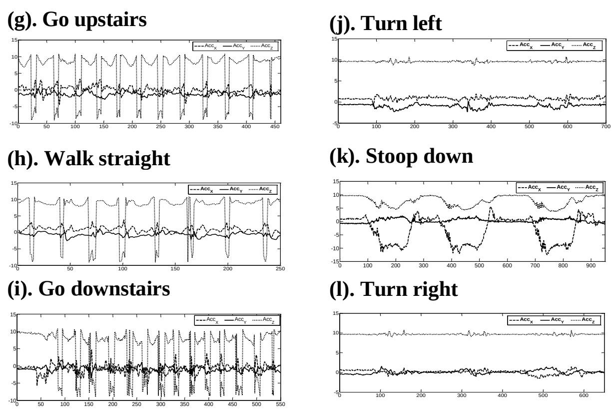

Figure 7. 3-DOF acceleration signals of each head motion at torso moving.

A. *Results and analysis*

Fig. 6 and Fig. 7 show sample 3DOF acceleration signals of each head motion from same participant, as indicated by Acc_x, Acc_y, and Acc_z. Fig. 6(a) is the acceleration waveform of *Nodding off*, which could be clearly differentiated from others except (b), the waveform of *head nod* (meaning yes motion). It is because both head motions are performed by the X-Z plane up-and-down moving, as illustrated in Table 1-a / b.

Since the differentiation of the motion is executed on a small microcontroller, computational burden should be limited. Therefore, using time-domain statistical feature could represent a first solution. To quantitatively identify the *Nodding off* motion from the other motions, a statistical process of all captured data is executed to compute the *mean*, *variance*, *standard deviation* and *signal energy*.

First of all, a cosine sliding windows is used to allow segmentation of each acceleration signal for each motion cycle. In order to reduce the acceleration amplitude impact (different for each participant and gesture), each segmented signal X, is normalized according to (3).

$$X_{nor} = (X - constant)/Max(|X|), \qquad (3)$$

where, X_{nor} is the normalized data segmentation. The *constant* of X-axis and Y-axis is set to zero, and the constant of Z-axis is set to 9.8 m/s^2. Then, the value of *mean*, *variance*, *standard deviation* and *energy* of X_{nor} are computed per DOF of the IMU. Three repeated cycles of each motion were extracted by participant, and then combined into a group. A total of nine dataset of each DOF and each motion was saved into database for comparison. Finally, an analysis of variance (one way ANOVA) were processed for the corresponding dataset of each motion to find the most appropriate value or dataset as "indicator" to identify the nodding off motion quantitatively.

Fig. 8 shows the normalized acceleration variance of X-axis with *p-value* at 4.73x10^{-10} and *F value* at 14.81. There is significant variance of acceleration in X-axis to discriminate the *Nodding off* from *Yes*, *No* and *Stoop down*. In Fig. 9, the normalized acceleration variance of Z-axis is presented with a *p-value* at 8x10^{-9} and *F value* at 12.38, which indicates that the *Nodding off* could be distinguished from the walking actions no matter straight, upstairs or downstairs. In conclusion, the acceleration variance of X-axis could be used to identify the *Nodding off* from the head motions at torso stillness, while the acceleration variance of Z-axis could be used to identify the *Nodding off* from the head motions at torso moving.

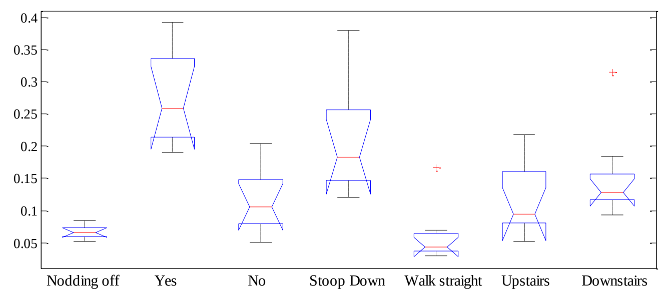

Figure 8. The normalized acceleration variance of X-axis

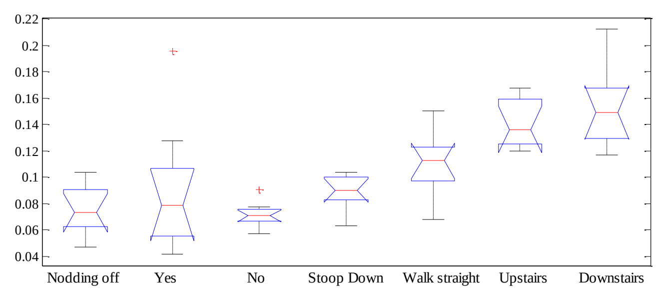

Figure 9.The normalized acceleration variance of Z-axis

B. *Risk level determination and discussion*

According to both equations (1) and (2), the risk level of accident is determined by head motion, EEG signal, as well as the occurrence of the head motion. The severity get score ranged from 1 to 9, representing low, middle and high levels. Of course, probability get a range between 0 and 1. As a result, a risk level determination and related actions are given in Table 2.

TABLE 2. RISK LEVEL DETERMINATION AND ACTION

Values	Risk Levels	Action
0 - 5	Low	Continue monitoring the status
6 - 10	Middle	Convey an alert to operator via vibrotactile motor
>10	High	**STOP** the machine tool or process

VI. CONCLUSION

In this paper, an intelligent system was proposed aiming at detecting the risk of the workers in an industrial facility. This system is centered on a Smart Safety Helmet (SSH) containing both IMU and EEG sensors. With the realized experiment, we show that using an accelerometer can identify the head motion caused by fatigue and sleepiness of workers. In the context of this work, the normalized acceleration variance of X-axis and Z-axis could be adopted as indexes to differentiate the risky motion from others. Data fusion with the EEG signal enhance the accuracy of the risk level evaluation by using severity table. Three actions is suggested as a function of the evaluated risk level: 1) no action to perform (low risk), 2) alert the user via haptic biofeedback such as vibration motor (medium risk) and 3) shut down the machine tool if the risk level breaks the high risk level.

In future works, the SSH system will be combined to a prediction of collision and collision avoidance algorithm for the process which includes robot. Therefore, based on the SSH system, an algorithm could control a tool, an industrial process, a robot or any workflow in order to reduce the risk.

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