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An experimental study of real-time identification of construction workers' unsafe behaviors

Yantao Yu[a], Hongling Guo[a,*], Qinghua Ding[b], Heng Li[c], Martin Skitmore[d]

[a] Department of Construction Management, Tsinghua University, Beijing, China
[b] Department of Computer Science and Technology, Tsinghua University, Beijing, China
[c] Department of Building and Real Estate, The Hong Kong Polytechnic University, Hong Kong
[d] School of Engineering and Built Environment, Queensland University of Technology (QUT), Australia

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ABSTRACT

Construction workers' unsafe behavior is one of the main reasons leading to construction accidents. However, the existing management approach to unsafe behaviors, e.g. Behavior-Based Safety (BBS), relies primarily on manual observation and recording, which not only consumes lots of time and cost but impossibly cover a whole construction site or all workers. To solve this problem and improve safety performance, an image-skeleton-based parameterized method has been proposed in a previous research to real-time identifying construction workers' unsafe behaviors. A theoretical framework has been developed with a preliminary test, but still lacking a comprehensive experiment to verify its validity, particularly in the recognition of the types of unsafe behaviors. This will have a serious impact on the extensive application of the method in real construction sites. Based on the method, this research designs and carries out a series of experiments involving three types of unsafe behaviors to examine its feasibility and accuracy, and determines the value ranges of relevant key parameters. The results of the experiment demonstrate the feasibility and efficiency of the method, being able to identify and distinguish unsafe behaviors in real time, as well as its limitations. This research not only benefits the extensive application of the method in construction safety management, but improves the effectiveness and efficiency of the method by identifying relevant future research focuses. Therefore this paper contributes to the practice as well as the body of knowledge of construction safety management.

1. Introduction

Nearly 80% of construction accidents are caused by workers' unsafe behaviors [25]. It is necessary and important for project managers or safety managers to monitor workers' unsafe behaviors in construction sites. Behavior-Based Safety (BBS) is regarded as a promising approach to managing unsafe behaviors on site [25,26]. BBS needs the observation and identification of on-site unsafe behaviors and then makes a feedback to jobsite workers [2,4,6,19,41]. However, this mainly depends on manual observation and recording, which not only consumes lots of time and cost but also impossibly cover a whole construction site or all workers [10], therefore limiting its extensive application in the construction industry.

Automation technologies have been proposed to monitor construction workers' behaviors in construction sites so as to improve the efficiency and effectiveness of unsafe behavior management [9,34,35]. For example, wearable sensors and motion capture technologies have been adopted in existing research [24,26,36]. The former is sensitive and in time, but affecting workers' normal working or operations [3,23,37,38]. The latter is usually to collect workers' behavior images with cameras and then identify unsafe behaviors by comparing the captured images with the images in unsafe behaviors databases [5,18,28,29,32,39]. The motion capture method requires no wearable devices, but not timely enough, as comparing the similarity of images is of great calculation amount [20,21,29,31,38,42].

Motion capture technologies have arisen the interest of the construction industry, being mainly used in the identification and biomechanical analysis of unsafe behaviors [15,33]. These methods usually contain four steps: 1) collecting sample data (joint sensor data, RGB-D image and stereo camera image), 2) reducing dimension, 3) extracting the features of motions from the sample data, and 4) identifying test motions by comparing their features with the features in Step 3 [7,11,12,14,22,27,32]. Most of these methods are post-analysis, thus not being applied to the real-time identification of unsafe behaviors. The main reason lies in the dimension reduction method. In order to reduce the redundant dimensions of images, previous studies used to

* Corresponding author.
E-mail address: hlguo@tsinghua.edu.cn (H. Guo).

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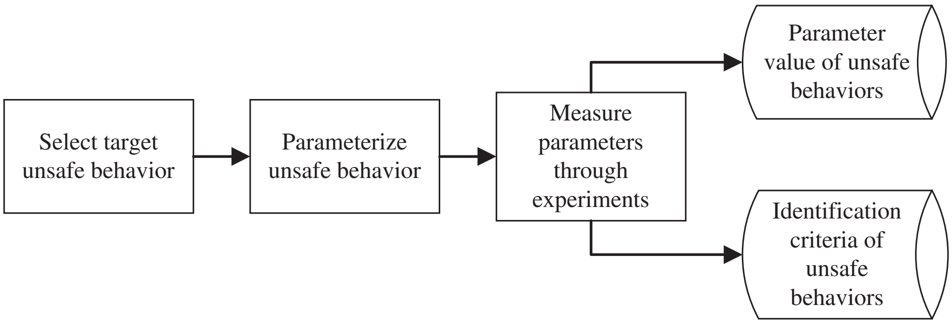


Fig. 1. Experiment process.

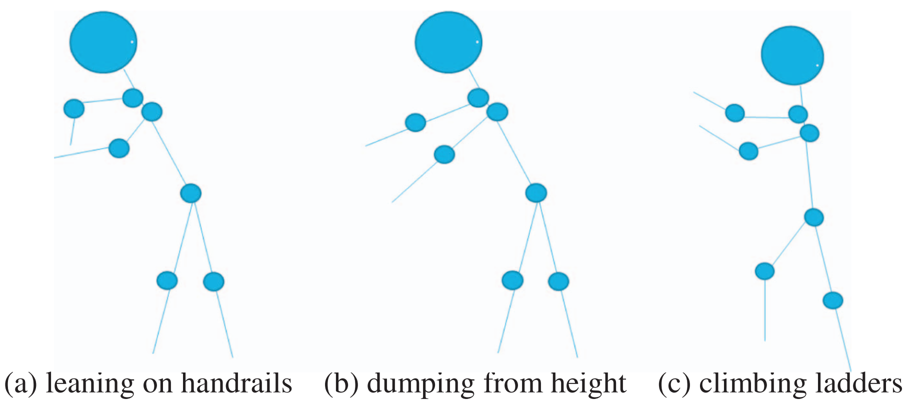


Fig. 2. The skeleton models of the leading postures of three unsafe behaviors.

Table 1
Key joint parameters in human skeleton mathematical model.

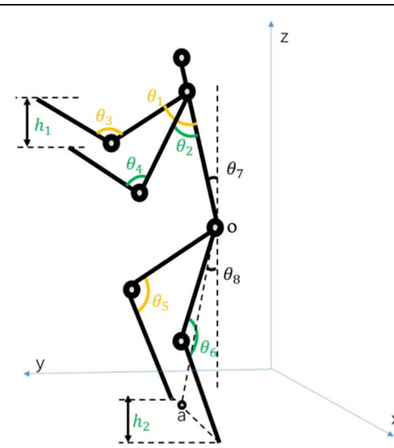
No.	Abbr.	Description	Skeleton model
θ1	LA	Angle between left arm and torso	
θ2	RA	Angle between right arm and torso	
θ3	LE	Angle of left elbow	
θ4	RE	Angle of right elbow	
θ5	LK	Angle of left knee	
θ6	RK	Angle of right knee	
θ7	UB	Inclination of upper body (Angle between torso and axis z)	
θ8	LB	Inclination of lower body (Angle between line a-o and axis z. Point a is the middle point of the connecting line between two feet; Point o is located at the hip joint.)	
h1	WH	The height difference between two wrists	
h2	AH	The height difference between two ankles	

Fig. 3. Kinect for Windows 2.0.

adopt machine learning methods, such as Kernal PCA and DTW methods [13,14]. However, this leads to long latency time since it took a lot of time to calculate the value of these features, especially in the case of dynamic behavior rather than static posture [8,11,13,14,23].To solve the above problems, a simplified image-based unsafe behavior identification method has been developed and tested with one behavior (climbing) of one worker by the authors. The preliminary study shows that it is feasible to real-time identify workers' unsafe behaviors through the simplification of behavior data and the development of a concise identification algorithm. However, various kinds of unsafe behaviors (e.g. dumping, leaning, etc.) are involved in a construction site with different characteristics, which mean different key parameters to describe these behaviors. Even for a same behavior with the same key parameters, different workers may present different value range for


Fig. 4. Leaning on a handrail.

these parameters when they do the same behavior. Therefore, it is necessary to further test whether or not the above-mentioned method is suitable for different kinds of unsafe behaviors as well as a same behavior for different workers.

Aimed at further testing the feasibility, accuracy and efficiency of this method, and recognizing the type of unsafe behaviors, a series of experiments were implemented in this research, which involves more than 30 testees and multiple unsafe behaviors. The results of this research can be used not only to further examine the validity of the method, but also to extend its application in the construction industry. This paper is structured as follows. First of all, the research method is presented, involving the brief introduction of the simplified image-based unsafe behavior identification method, and then the experiments described and data collected. Following this, the results are presented and further discussed, the future research also proposed. Finally, a conclusion is drawn.

2. Research method

A real-time image-skeleton-based method was proposed to identify and recognize construction workers' motion behaviors. The key conception is leading posture, which is the precursor of an unsafe behavior. For example, dumping construction wastes from height is a dangerous behavior. The leading posture of this behavior could be to lift up arms when standing near the floor edges. Once the posture occurs, it means that a worker is going to dump something from height, thus leading to an unsafe behavior. This moment is also the optimal time to warn the worker, as she or he is sure to dumping from heights but not yet. As there is time lag between a leading posture and an unsafe behavior, as long as a leading posture can be identified in real time, relevant unsafe behavior can be identified and prevented by sending workers alarm messages immediately.

The concept of leading posture simplifies a dynamic unsafe behavior to a static leading posture, which is the precursor of an unsafe behavior and able to be further simplified as vital joint parameters by referring to the mathematical model of human skeleton [8], and then capture and compare the value of relevant parameters with their standard value determined in advance to judge whether or not the behavior is safe. By this, a complex behavior can be simplified as several parameters, which shortens the identification time considerably.

To further test the accuracy and efficiency of the method, a series of experiments were conducted in this research according to the following process shown in Fig. 1. First, typical and common unsafe behaviors were selected as the research objects, then parameterized according to the mathematical human skeleton model [16]. Furthermore, the parameter value and identification criteria of unsafe behaviors were determined through the experiment.


Fig. 5. Dumping from height.

Fig. 6. Climbing a ladder.

2.1. Selection and parameterization of unsafe behaviors

There are different kinds of unsafe behaviors in the construction site, such as climbing without permission, sleeping on sills, pulling trolleys on stairs, etc. [30]. By referring to Ref. [30], a casebook of cause analysis of construction accidents in China, leaning on handrails, dumping from height, and climbing ladders were selected in this research (see Fig. 2), as they were three commonly-seen unsafe behaviors leading to construction accidents. On the other hand, these behaviors were easy to be identified, thus being more practical choice for this preliminary research. What's more, the similarity between leaning and dumping can be used to test the method's ability to distinguish different behaviors. In order to realize the real-time identification of these behaviors, they need to be simplified as some leading postures, that is leaning out, dumping and climbing.

The three leading postures were then simplified as human skeleton models (see Fig. 2), which may be described by several key parameters. According to the theory of human skeleton model, the posture of human body was determined by joints [16]. Specifically, this research referred to the idea of 3DSSPP model [1], which defines human postures by regulating the angle of joints. The key joint parameters were selected to identify and recognize these three unsafe behaviors (see Table 1).

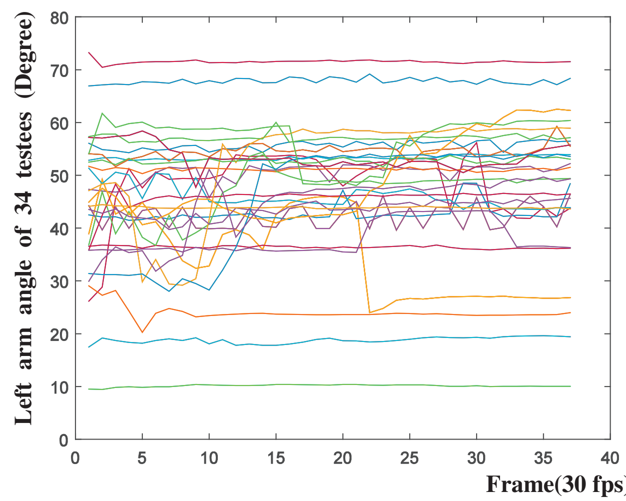


Fig. 8. The value of 34 testees' left arm angle when leaning on the handrail.

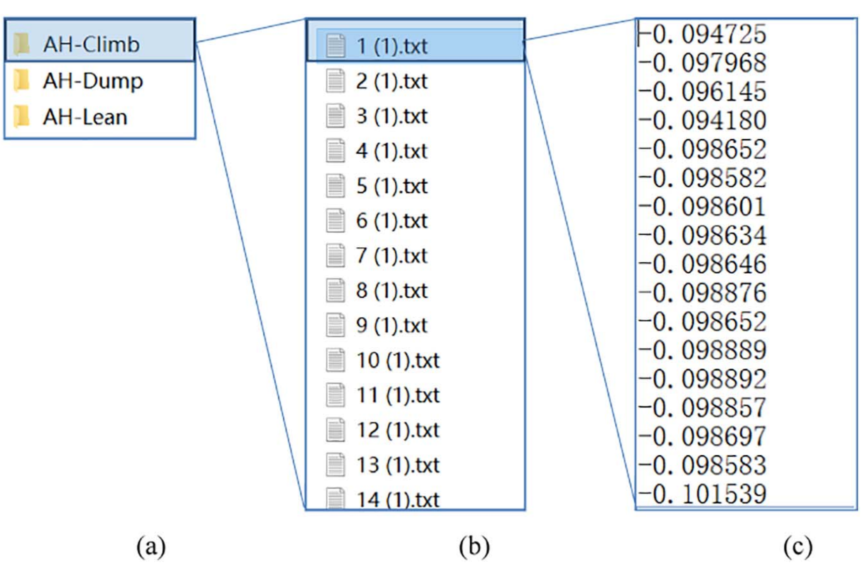


Fig. 7. A part of the original data.

Table 2
The confidence intervals of 34 testees' ankle height difference during dumping.

Testee no.	Dumping/ankle			
	θ	Confidence interval		Confidence coefficient
		θ − δ	θ + δ	
1	− 0.046	− 0.049	− 0.043	0.931
2	− 0.092	− 0.092	− 0.092	0.724
3	− 0.053	− 0.061	− 0.045	0.759
4	− 0.088	− 0.088	− 0.088	0.621
5	− 0.103	− 0.103	− 0.102	0.724
6	− 0.088	− 0.088	− 0.087	0.724
7	− 0.097	− 0.099	− 0.096	0.793
8	− 0.082	− 0.083	− 0.082	0.621
9	− 0.082	− 0.083	− 0.082	0.621
10	− 0.046	− 0.048	− 0.045	0.931
11	− 0.079	− 0.080	− 0.078	0.759
12	− 0.099	− 0.099	− 0.098	0.724
13	− 0.090	− 0.090	− 0.089	0.793
14	− 0.094	− 0.094	− 0.094	0.655
15	− 0.079	− 0.080	− 0.079	0.793
16	− 0.078	− 0.078	− 0.078	0.828
17	− 0.102	− 0.106	− 0.097	0.793
18	− 0.039	− 0.044	− 0.035	0.690
19	− 0.096	− 0.097	− 0.096	0.690
20	− 0.086	− 0.086	− 0.085	0.862
21	− 0.081	− 0.081	− 0.081	0.793
22	− 0.081	− 0.081	− 0.080	0.759
23	− 0.083	− 0.084	− 0.082	0.621
24	− 0.074	− 0.074	− 0.074	0.828
25	− 0.092	− 0.093	− 0.092	0.793
26	− 0.089	− 0.090	− 0.088	0.621
27	**− 0.083**	**− 0.104**	**− 0.062**	**0.793**
28	− 0.098	− 0.099	− 0.098	0.759
29	− 0.093	− 0.095	− 0.092	0.931
30	− 0.080	− 0.084	− 0.077	0.759
31	− 0.094	− 0.094	− 0.094	0.862
32	− 0.092	− 0.092	− 0.091	0.759
33	− 0.076	− 0.101	− 0.052	0.655
34	− 0.085	− 0.085	− 0.084	0.586

Table 3
The value ranges of joint parameters of the leading postures of three unsafe behaviors.

Behavior	LA	LE	LK	RA	RE	RK	UB	LB	AH	WH
Leaning	10	0	110	25	80	140	10	5	− 0.1	0
	75	180	180	70	160	180	40	30	− 0.05	0.015
Dumping	25	40	110	30	100	150	5	5	− 0.11	0
	80	180	180	70	180	180	35	25	− 0.04	0.025
Climbing	30	120	80	40	40	110	10	13	− 0.11	0
	85	180	180	110	180	180	35	30	− 0.03	0.015

2.2. Determination of value range of leading posture parameters

With the selection of key parameters, their value ranges (i.e. standard value) need to be determined to aid in the identification of leading postures and unsafe behaviors further. Considering that the value of a same leading posture parameter values may vary from one person to another, a series of experiments were implemented to measure the value ranges of the leading posture parameters. A leading posture of unsafe behavior can be identified if the value of relevant parameters is in the pre-defined ranges, as explained in Section 3.2.

2.3. Recognition of unsafe behaviors

In addition to the identification of unsafe behaviors, the captured data can also be used to recognize the type of unsafe behaviors, i.e. to analyze not only whether or not a behavior is safe, but also what the leading posture of the unsafe behavior is (e.g. climbing, leaning, etc.). This will help reveal the causes of construction accidents and improve the performance of safety training, therefore benefiting the implementation of BBS.

The data captured in the experiments was used to determine the parameters, which could be as the criteria of recognizing the type of unsafe behaviors. First, the value ranges of parameters related to each unsafe behavior's leading posture are measured. Then through the comparison of the value ranges of parameters for different behaviors, the parameters that distinguish one behavior with the others can be selected. These parameters are used as "feature parameters" to determine what an unsafe behavior is when the unsafe behavior is identified.

2.4. Data acquisition

Kinect for Windows 2.0, as shown in Fig. 3, was adopted in this research to collect the testees' posture data. Kinect contains multiple infrared sensors, which may measure the distance between one point and the infrared sensors, thus the location of the point can be calculated with the distances to the sensors.

Compared with traditional RGB-video-based methods, Kinect has the following two advantages.

1) Kinect provides less redundant data. Kinect provides only depth frames, which contain enough information for posture detection, but the amount of data is much less than RGB images, thus facilitating the rapid detection of posture.
2) Kinect doesn't require training period. Kinect directly provides the parameters of human body skeleton, including the value of joint parameters. On the contrast, the RGB-video-based methods are usually based on machine learning method, including the model training period. Due to the complexity of construction sites, it may need thousands of images to train the model. What's more, the latency time of RGB-based methods are longer, which is usually several seconds, even tens of seconds.

Through the use of the algorithms provided by Microsoft, human body joints can be identified from the depth image. Then by retrieving the position data of human body joints, human body skeleton can be generated [17]. What's more, according to the fact that Kinect works well with XBox, its motion capture and identification is accurate and real time, therefore acceptable.

3. Experiments and analysis

3.1. Experiment process

34 male students participated in the experiments, their heights range from 162 cm to 203 cm. Each student was required to perform the three behaviors with their own habits. The details are described as follows:

1) Leaning on a handrail, as shown in Fig. 4;
2) Dumping from height, which was simulated by holding an empty box and dumping it from the handrail (see Fig. 5); and
3) Climbing, which is simulated by climbing a ladder against a wall (see Fig. 6).

The Kinect camera fixed on a tripod recorded and stored the posture data when the students performed required behaviors. To make sure the accuracy and stability of the captured data, the students were required to keep a position for 10 sec or so once they performed a required behavior.

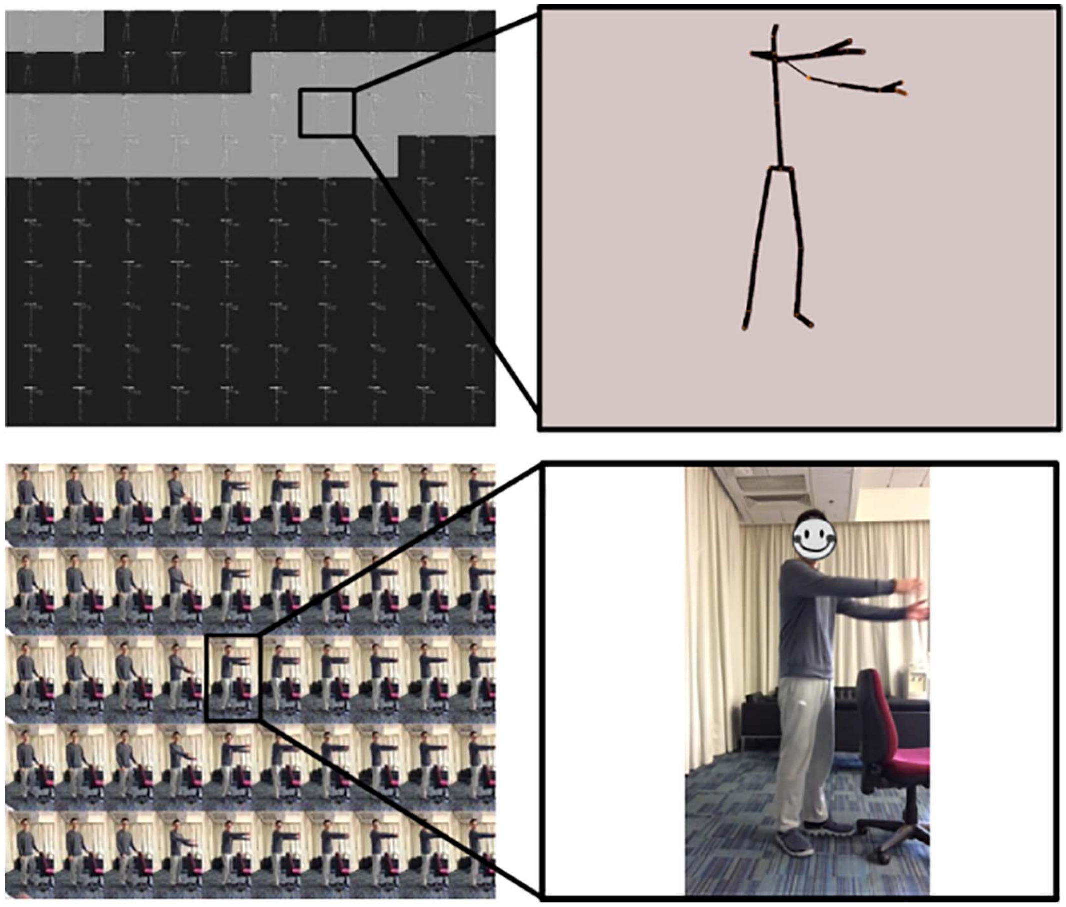


Fig. 9. The comparison between Kinect frames and common camera frames.

Table 4
The accuracy and error rate of the method.

Posture	Sample	Safe		Unsafe		Total	Accuracy	Error Rate	Type I Error	Type II Error
		White	Black	White	Black					
Climb	1	26	1008	363	132	1529	89.67%	10.33%	8.63%	1.70%
	2	75	545	206	69	895	83.91%	16.09%	7.71%	8.38%
	3	135	1747	412	320	2614	82.59%	17.41%	**12.24%**	5.16%
	4	0	2141	43	116	2300	94.96%	5.04%	5.04%	0.00%
	Sum	236	5441	1024	637	7338	88.10%	11.90%	8.68%	3.22%
Dump	1	505	1935	930	895	4265	67.17%	32.83%	**20.98%**	**11.84%**
	2	670	1640	645	55	3010	75.91%	24.09%	1.83%	**22.26%**
	3	30	2203	1120	70	3423	97.08%	2.92%	2.04%	0.88%
	4	553	2321	676	104	3654	82.02%	17.98%	2.85%	**15.13%**
	Sum	1758	8099	3371	1124	14,352	79.92%	20.08%	7.83%	**12.25%**
Lean	1	86	1485	523	307	2401	83.63%	16.37%	**12.79%**	3.58%
	2	0	2007	771	674	3452	80.48%	19.52%	**19.52%**	0.00%
	3	30	1109	400	0	1539	98.05%	1.95%	0.00%	1.95%
	4	402	4003	763	1352	6520	73.10%	26.90%	**20.74%**	6.17%
	Sum	518	8604	2457	2333	13,912	79.51%	20.49%	**16.77%**	3.72%
Total		2512	22,144	6852	4094	35,602	**81.44%**	18.56%	**11.50%**	**7.06%**

3.2. Statistical processing and analysis of data

Fig. 7 presents a part of the stored data. The folder in Fig. 7(a) contains all of the 34 testees' data of one certain joint for the leading posture of one certain behavior. For example, *AH-Climb* means the ankle heights when the testees were climbing. Each *.txt* format file in Fig. 7(b) includes the data of one testee, which is shown in Fig. 7(c), captured 30 times per second.

The primary data was statistically processed and analyzed to facilitate the identification and recognition of the leading postures of unsafe behaviors. Fig. 8 shows the data of the 34 testees' left arm angle when they were leaning on the handrail. Each curve represents one testee's data. The range of left arm angle during leaning can be easily identified from the diagram, that is between 10 (the minimum value) and 75 (the maximum value). The value of joint parameters of the leading postures of three unsafe behaviors is shown in Appendix A.

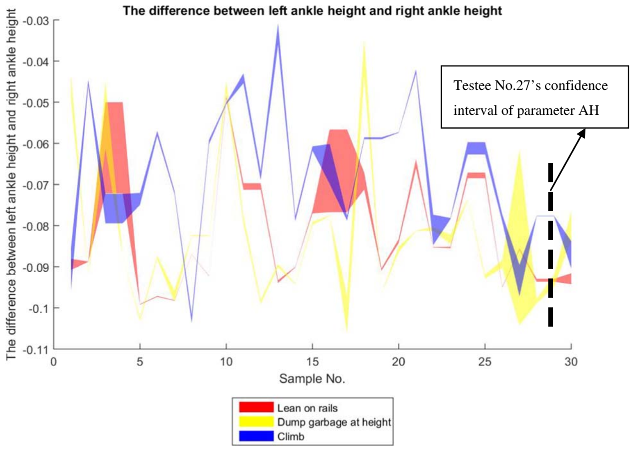


Fig. 10. The confidence intervals of the difference between two ankle heights. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

Table 2 shows the analysis results of ankle height differences of the leading posture of *dumping* behavior, each row represents one testee's data, including average θ, confidence interval [θ − δ, θ + δ] and its confidence coefficient, as well as confidence interval [θ − 2δ, θ + 2δ] and its confidence coefficient. Feature parameters were identified through comparing the confidence intervals of the leading postures of different behaviors to recognize unsafe behavior, and the details will be introduced in Section 3.4.

Table 3 provides the criteria of unsafe leading postures. If a worker's posture satisfies these criteria, it means that the worker is performing the leading posture of an unsafe behavior, that is the worker is going to conduct the unsafe behavior.

3.3. Identification of unsafe behaviors

As mentioned above, unsafe behaviors can be identified if the value of relevant joint parameters falls into the value ranges of key parameters of the leading postures of unsafe behaviors. The critical issue is to determine the value ranges. As the example shown in Fig. 8, the value range of left arm angle when leaning is easily determined via considering the minimum and maximum value as well removing some noisy points. Therefore, according to all of the joint parameter value of three unsafe behaviors during experiment, relevant value ranges are gotten as shown in Table 3. Furthermore, it was found that when each of the testees was randomly doing one of the three unsafe behaviors again, the unsafe behaviors could be identified accurately and rapidly. This means that once the value of key parameters of a certain behavior satisfies relevant value ranges, the behavior is identified as an unsafe behavior in real time, thus improving the efficiency of image-based behavior identification.

What's more, four people were involved in the test to further examine the accuracy and efficiency of the proposed method. During the experiment, the testees were required to conduct one of the three unsafe behaviors according to predefined commands, and conduct random behaviors without any commands. A common camera and a Kinect camera recorded the testees' behavior concurrently at the same frequency of 30 fps. According to the above approach, when joints' angles satisfied the unsafe behavior criteria in Table 3, the screen would change from black to white. It means that relevant testees were to do unsafe behaviors. Then the RGB videos collected by the common camera and the depth videos collected by the Kinect camera were divided into frames. The depth images were compared with the common images frame by frame to examine whether this approach provided right judgment, as shown in Fig. 9.

The depth images involved white images and black images. The white ones were judged as unsafe behaviors, while the black ones were judged as safe behaviors. The RGB images were identified as safe or unsafe behaviors artificially. Thus, the judgment results can be divided into four categories: 1) black safe behaviors, 2) white unsafe behaviors, 3) white safe behaviors, and 4) black unsafe behaviors. The first two categories are right judgments, while the last two are wrong. Specifically, Situation 3) means that the approach wrongly recognize safe behaviors as unsafe behaviors, which belongs to the error of Type I; while Situation 4) means that the approach failed to identify the unsafe behaviors, which belongs to the error of Type II. The test results are listed in Table 4. It can be seen that the total accurate rate is up to 81.44%, the error rate of Type I and Type II 11.5% and 7.06% respectively.

3.4. Recognition of unsafe behaviors

In order to improve construction safety performance, it is significant to know which type of unsafe behavior leads to construction accidents in addition to just knowing an unsafe behavior occurring. As mentioned above, the confidence intervals of key parameters were used to recognize unsafe behaviors. For example, according to Table 2, Testee 27′s confidence interval of the parameter *AH* of dumping is [− 0.104, − 0.062], which is represented by the black dot line in Fig. 10. The yellow region is generated by plotting the AH confidence intervals of all the 34 testees when dumping. The red and blue regions represent respectively the cases of leaning the handrail and climbing the ladder. Via referring to the overlap of these regions, the parameter *AH* can be judged as a feature parameter or not to recognize the type of unsafe behaviors.

Fig. 11 shows the confidence intervals of all joints parameters for performing the three unsafe behaviors. According to these figures, if two regions of different colors in a same figure have no overlaps, it is considered that the parameter represented in the figure can be used as a feature parameter to distinguish the two behaviors represented by the two regions of different colors. In this research, the blue region in Fig. 11(g) has no overlaps with the yellow region and red region. As blue, yellow and red regions respectively represent *climbing*, *dumping* and *leaning*, *left elbow angle* can be used as the feature parameter to distinguish *climbing* from *dumping* and *leaning*. Then in Fig. 11(i), there is rather less overlap area between the red and yellow region, then *left knee angle* can be used to distinguish *leaning* and *dumping*.

In this research, both *left elbow angle* and *left knee angle* are taken as the feature parameters to recognize unsafe behaviors, the process of recognition is shown in Fig. 12. When an unsafe behavior is identified, the value of *left elbow angle* (α) is checked at first. If the value is in the range from 125 to 180, which is determined based on the volume of overlaps, the unsafe behavior will be judged as *climbing*; otherwise, the unsafe behavior is regarded as *leaning* or *dumping*. In this case, the *left knee angle* (β) will be checked. If the value is between 50 and 130, the behavior will be judged as *leaning*; or, *dumping*. The method was also tested during the experiment, it helped recognize each of the three unsafe behaviors to some extent.

4. Discussion and limitations

4.1. Discussion

Table 4 shows the accuracy and error rate of the unsafe behavior identification method. The total accurate rate of all of the tests is

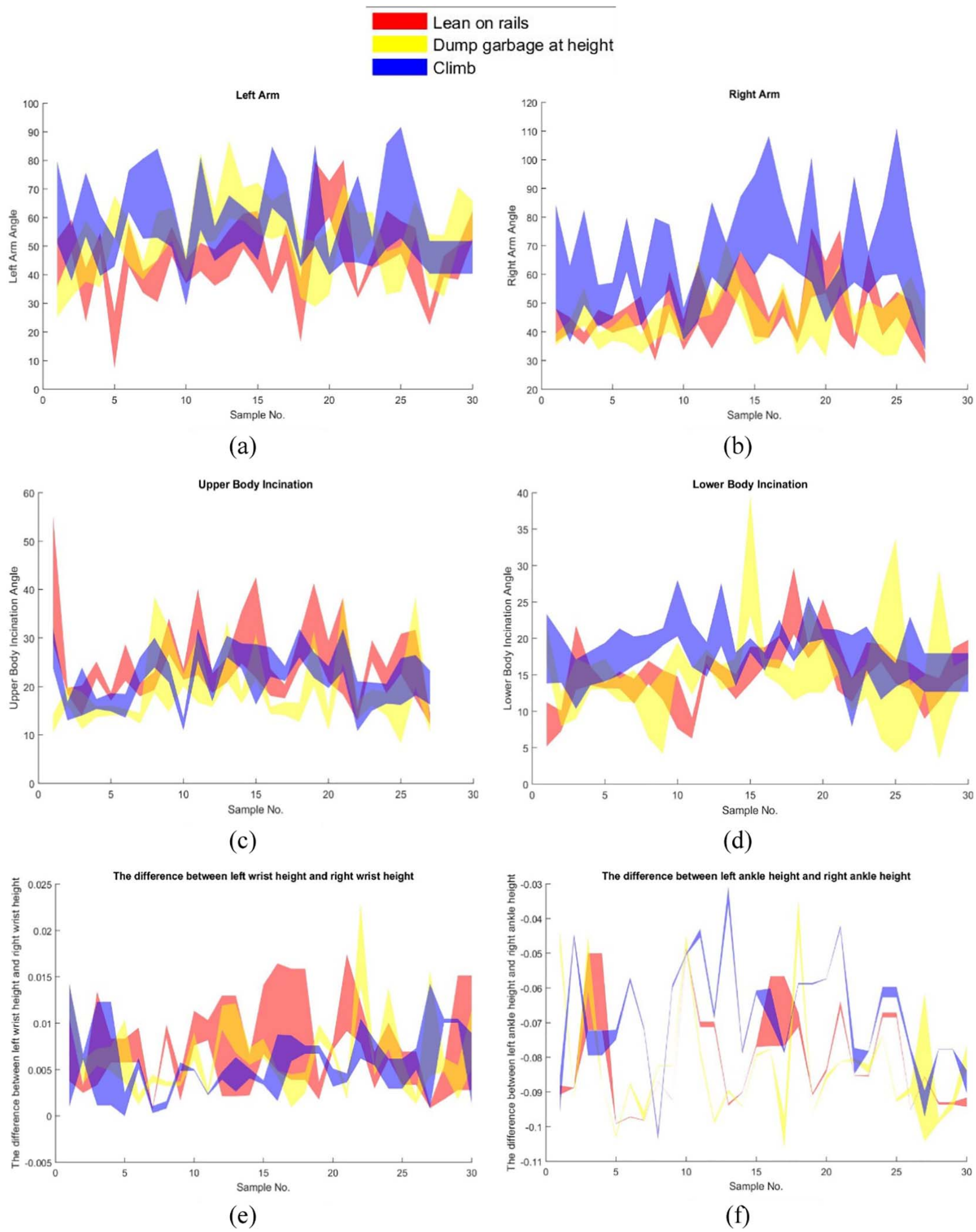


Fig. 11. Confidence intervals of all joints parameters of three unsafe behaviors. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

81.44%, and the total error rate is 18.56%. It can be found from the table that several tests contribute much more to the error rates than the others, including climb3, dump1, dump2, dump4, lean1, lean2 and lean4. A detailed scrutiny was conducted to reveal the causes of the relatively high error rates by analyzing the misunderstood safe behaviors (Type I) as well as the ignored unsafe behaviors (Type II). The following two reasons were identified to be responsible for the wrong judgment.

1) Obstacles between Kinect and joints

Some curves in the tables in Appendix A fluctuate sharply, which means that the parameters provided by Kinect are not always stable or accurate. The reason is the obstacles between Kinect camera and joints. For example, the right leg of the testee in Fig. 13 was the obstacle between the Kinect camera and the left leg, leading to the angle of left knee larger than 180°, exceeding the normal range.

2) Lack of parameters

Another reason of error judgments is the lack of parameters.

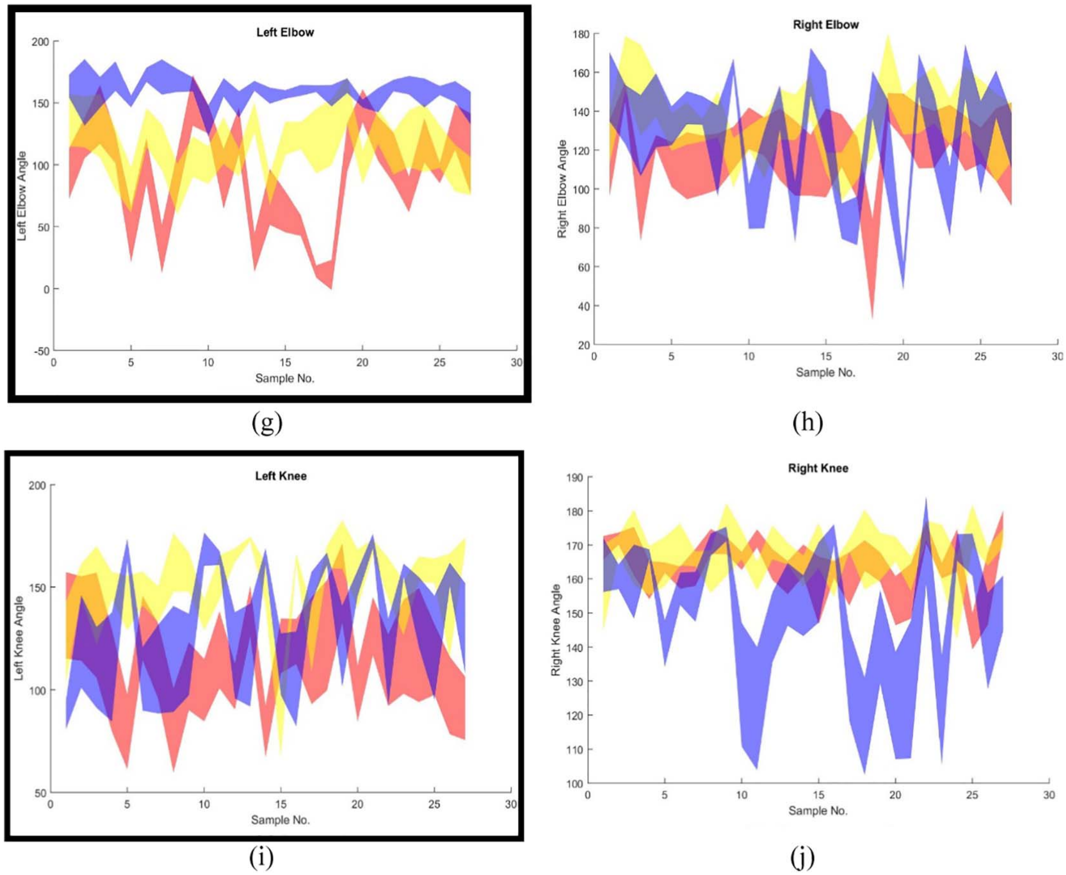


Fig. 11. (*continued*)

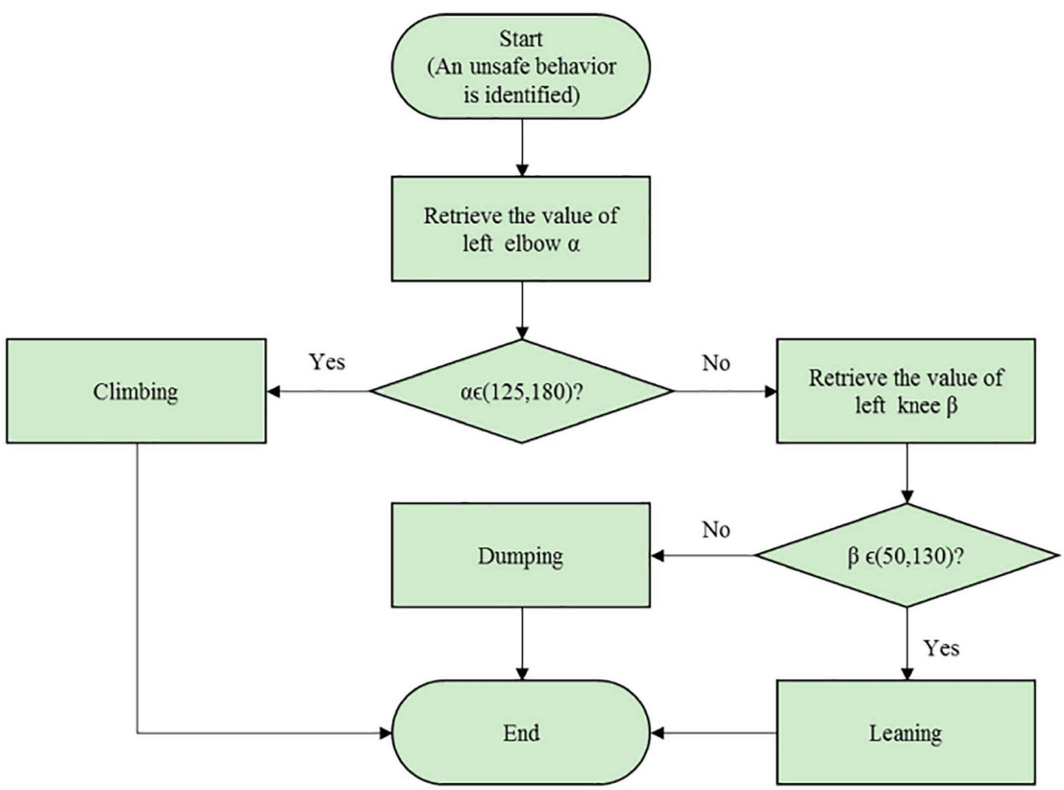


Fig. 12. The process of recognizing the type of unsafe behaviors.

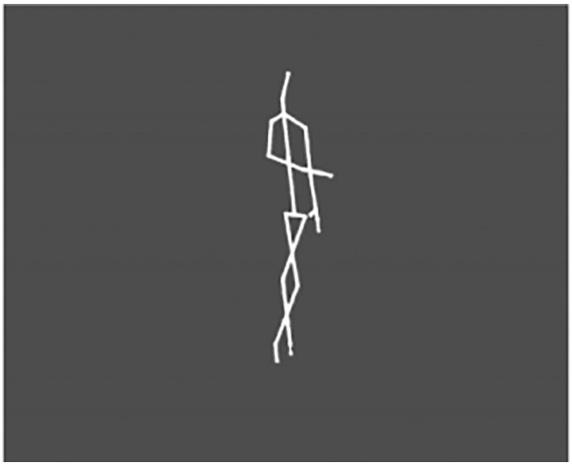


Fig. 13. The obstacles between Kinect camera and joints.

Inadequate parameters enlarged the scope of unsafe behaviors, thus leading to the error of Type I, which judges safe behaviors as unsafe. Fig. 14 is a typical example in the dumping test. (a) Is the standard dangerous behavior of dumping, while (b) is also considered as unsafe. The reason is that in Table 3, the standard of dumping behavior contains only one parameter (the arm angle) to describe the rotation of shoulder joints. However, the shoulder joint is a sphere joint, which can rotate around two axes. Thus to increase the judgment accuracy further, more parameters need be considered in the future.

4.2. Limitations

With the development of the image-based unsafe behavior identification and recognition method, its functions are further improved and tested in this research. The method, to a large extent, has enabled the identification and recognition of unsafe behaviors in real time, but some limitations were also exposed during data collection and analysis.

1) Unstable data

During the process of data collection, the testees were required to be still, the value should be constant or relevant stable, i.e. the line of value should be straight and horizontal. However, it can be seen from Appendix A that the value of a same parameter for a same testee fluctuates in a large range. This may affect the performance of identification and recognition of unsafe behaviors. The following two reasons identified involves: a) the system error of the Kinect camera, which accounts for the fluctuation in a narrow range, and b) the obstacles between the camera and the joints, which accounts for the fluctuation in a wide range. The Kinect camera collected data with some infrared sensors. If there exist some obstacles between a camera and a target, the infrared light will be blocked, and therefore the observed data will deviate a lot from the actual value. In the experiment, the camera was set on the right of the testees when they were leaning or dumping, and on the left when climbing. As a result, the left part of climbing data, e.g. left elbow, left arm and left knee, and the right part of leaning and dumping data, fluctuate in a smaller range than the other parts. Therefore, the solution to collect data needs to be improved in the future.

2) Lacking height calibration

In order to make the value range of leading posture parameters suitable for different height of workers, this research selected different height of testees (from 162 cm to 203 cm) to collect relevant data. However, this may affect the accuracy of Kinect, since Kinect was not calibrated according to the testees' height. To achieve more accurate data from Kinect, a calibration will be needed in the future research.

3) Inadequate feature parameters for behavior recognition

Only two feature parameters, i.e. *left elbow angle* and *left knee angle*, are selected to distinguish the three unsafe behaviors in the experiment. In fact, there are more unsafe behaviors which need to be identified and recognized in the construction site, thus more feature parameters needed. However, it can be found from Fig. 11 that most of the parameters cannot be used as the feature parameter since the value of different parameters overlaps a lot. This needs to further explore how to recognize more unsafe behaviors in the future research.

In addition to posture information, other information, especially workers' location, is also needed to aid in the accurate identification of unsafe behaviors. Taking the example of climbing a concrete mixer when it is working, even the proposed method is able to identify the climbing behavior, it cannot judge what the worker is climbing. This problem can be solved by comparing the locations of the worker and the concrete mixer.

4) Lacking test in practice

The experiment was still conducted in a virtual construction environment, which is much simpler than a real construction site which commonly involves more workers and obstacles (e.g. building components, construction machines, temporary supports, etc.). This may influence the performance of identification and recognition of workers' unsafe behaviors. Therefore, it is necessary to test the availability of the

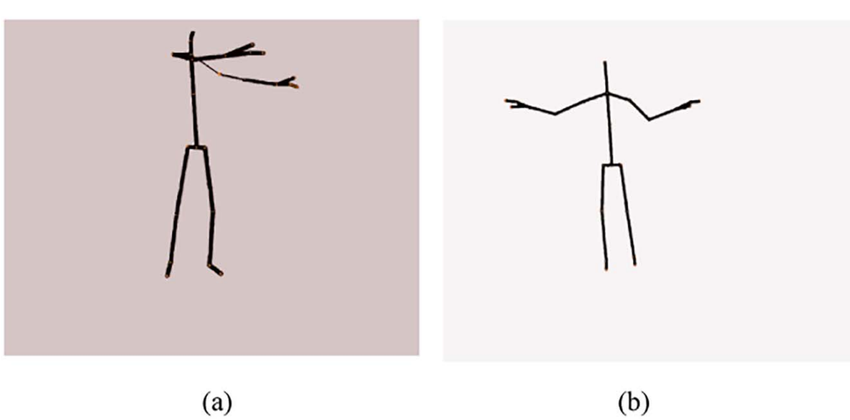


Fig. 14. Lack of parameters leading to Type I error.

identification method in the construction site in the future.

5. Future work

With the discussion of limitations of the image-based unsafe behavior identification method, the future work to improve the method is presented as follows.

5.1. Utilization of multiple cameras to collect the data

The captured data is not accurate enough if there exist some obstacles between a camera and a target, e.g. human body, handrails, ladders, etc. To improve this, multiple cameras can be used at the same time to collect the data. For example, in the experiment, the Kinect camera was set on the right side of the testees, resulting in large error of data related to left body. In this case, another Kinect camera can be placed on the left of the testee to capture the data of left body to improve the accuracy of data. Therefore, the solution to use multiple cameras to collect data will be explored in the future research.

5.2. Selection of more feature parameters to recognize unsafe behaviors

Ten parameters were selected as the potential feature parameters to recognize the three unsafe behaviors, but only two of ten parameters are available. This is not enough to differentiate three behaviors above. To solve the problem, the value of more parameters should be captured during the experiment to find out more appropriate feature parameters of different behaviors. In fact, the parameters used in the experiment are only a small part of what Kinect provides. As Kinect provides the 3D (three-dimensional) coordinates of all of the joints, the parameters like joint positions, angles or distances between any two joints can be calculated in real time [40]. In the future research, more construction unsafe behaviors will be selected and analyzed to determine more feature parameters.

5.3. Test of the method in a real construction environment

In order to further evaluate the validity of the method, more tests in real construction sites are needed. In the near future, the method as well as several selected unsafe behaviors will be tested in some real construction sites. Otherwise, the calibration based on different height of testees will be conducted to improve the availability of the method.

6. Conclusion

An image-based method for the real-time identification of construction workers' unsafe behaviors was developed. The original contribution of this research is to propose an early unsafe behavior identification method by identifying relevant leading postures as well as their parameters, determining the standard value range of the parameters, and developing the process of behavior identification. The kernel conception is leading posture, which advances the moment of identifying unsafe behaviors by simplifying a dynamic behavior to a static posture. This makes it possible to conduct early-warning for unsafe behaviors in real time.

Compared with previous research on behavior identification in the construction industry, the most important feature of the proposed method lies in its timeliness, thus providing a potential of unsafe behavior monitoring in real time as well as warning in advance. The main reasons for this are: 1) that infra-red video, rather than ordinary video, is selected as the data source, reducing the data-processing load; 2) that the built-in algorithms in Kinect could provide immediate joint value; and 3) that dynamic behaviors are simplified to joint values, making the judge criteria very simple.

In order to further test its feasibility, accuracy and efficiency for different types of unsafe behaviors, a comprehensive experiment is conducted in this research. Three types of unsafe behaviors, such as leaning, dumping and climbing, and 34 testees are selected to test the method. Through the analysis of the data collected during experiment, the value ranges of key parameters for each of these behaviors are built to support the identification of unsafe behaviors (i.e. safe or not), the two feature parameters (i.e. *left elbow angle* and *left knee angle*) achieved to aid in the recognition of unsafe behaviors (i.e. the type of a behavior). The result shows that the method is able to identify one of these three unsafe behaviors as well differentiate them in an efficient way, thus having a potential to support workers' behavior management in the construction site. On the other hand, some limitations are also exposed, such as unstable data, inadequate feature parameters, and so on. With this, the future research work is also identified to improve the performance of the method. Thus this research not only extends the use of the method in construction safety management practice, but also contributes to the foundational research into worker behaviors, e.g. BBS, as well as the continuous improvement of the image-based identification method.

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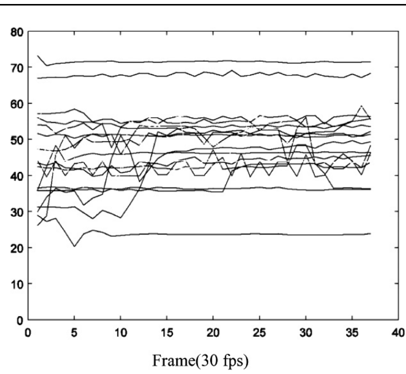
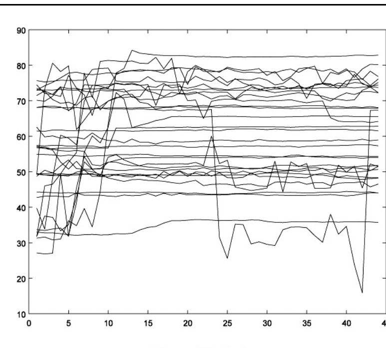
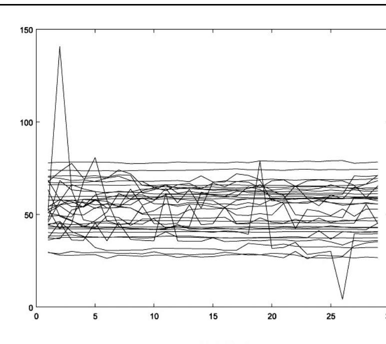
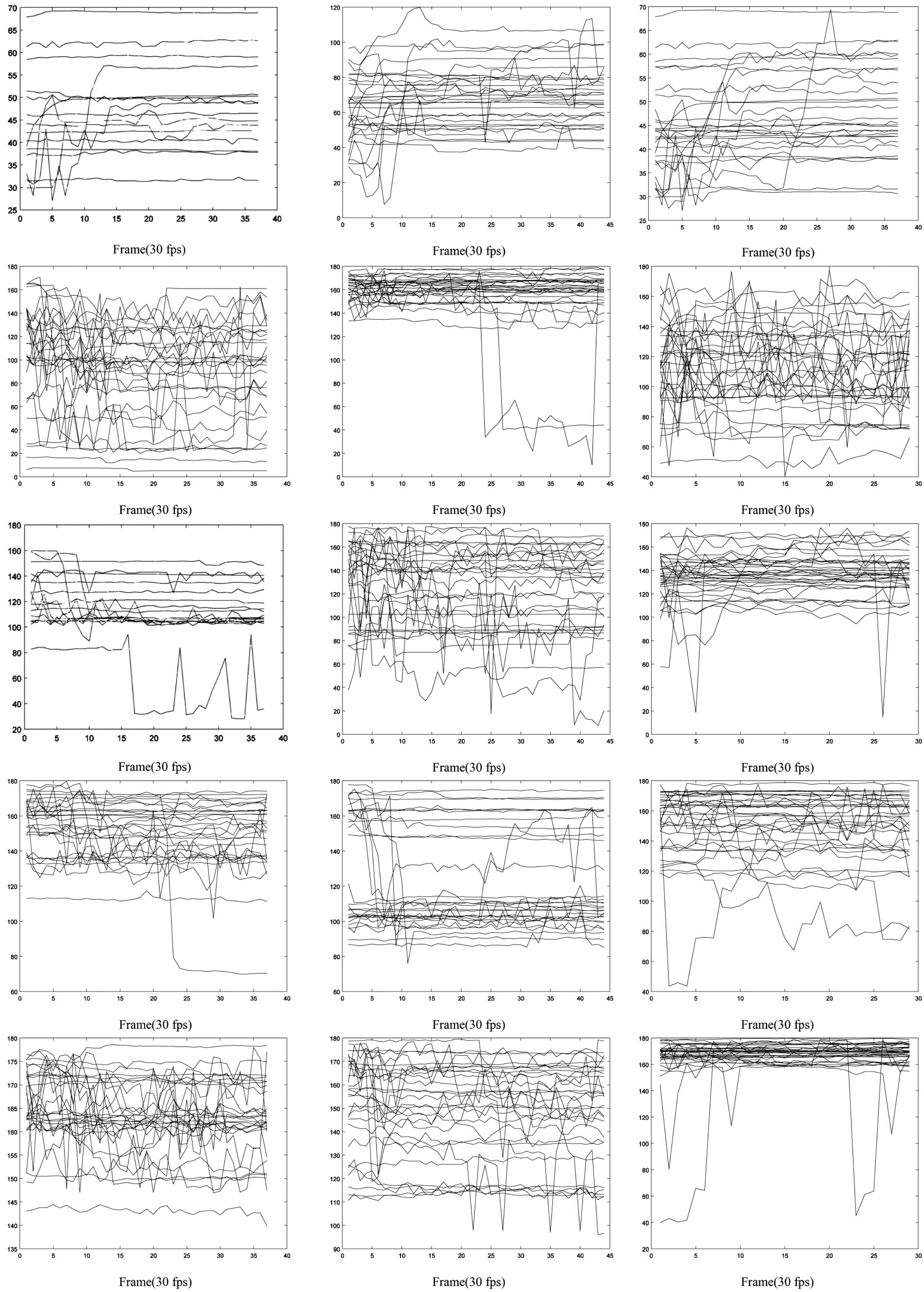
Appendix A. The value of joint parameters of the leading postures of three unsafe behaviors

Parameter	Leaning posture	Climbing posture	Dumping posture
LA (degree)			
RA			

(degree)



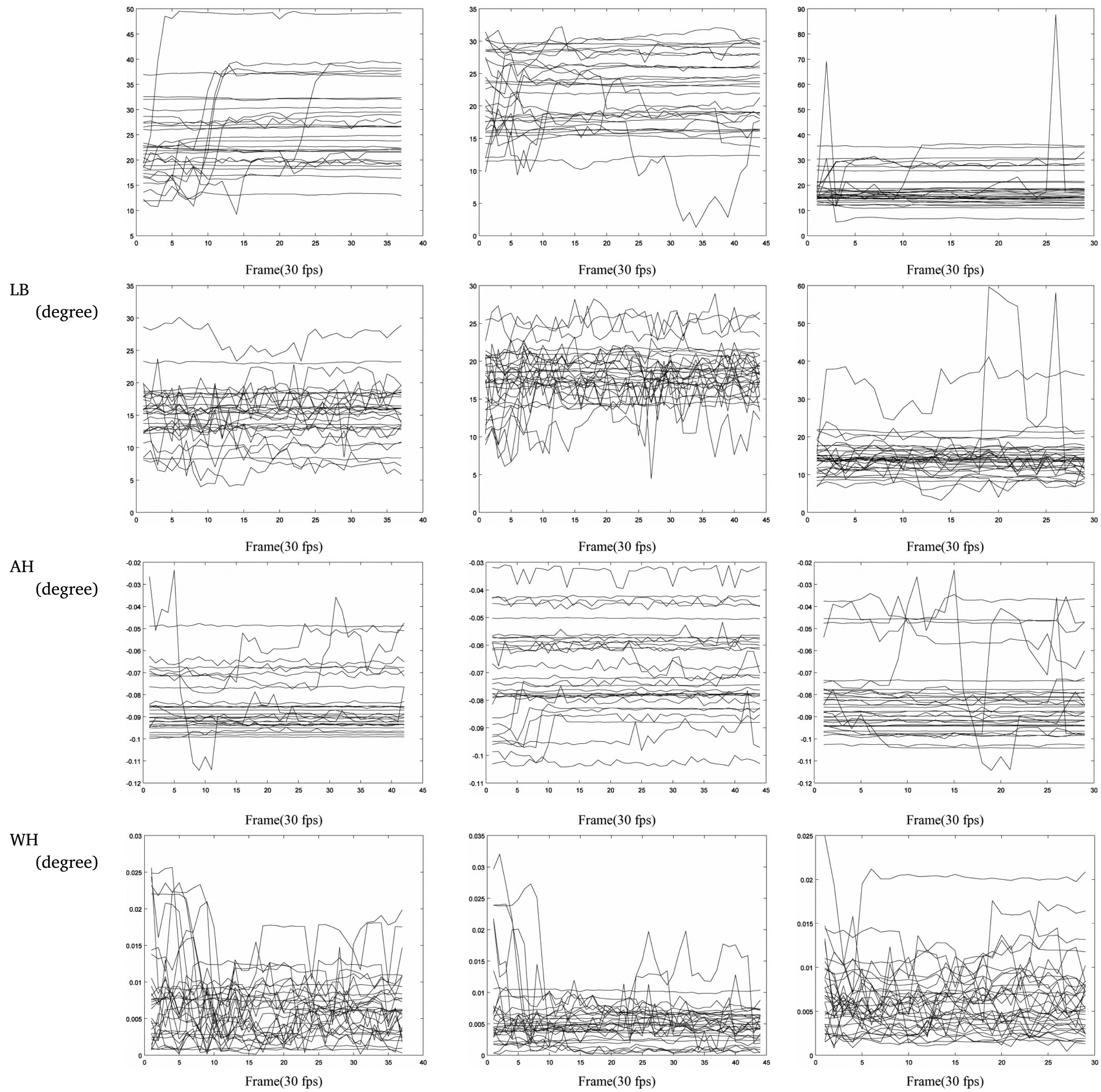
LE
(degree)

RE
(degree)

LK
(degree)

RK
(degree)

UB
(degree)



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