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RESEARCH ARTICLE

The evaluation of depth image features for awakening event detection

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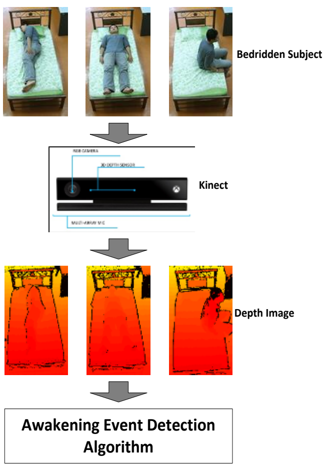
Graphical abstract



Abstract

Falls among bedridden would increase in number if they are left unsupervised by the caregivers. Fall might occur among the bedridden person especially elderly which is about 30% of those over 65 years and 40% of those over 80 years. From the total number of falls happen, bedroom can be considered as one of the most common falling location The aim of this study is to evaluate the features from the Kinect-like depth image representing the bedridden in detecting the awakening event as the event that falls might occur. The images from 20 subjects performing six sleeping activities including the awakening events were obtained before image segmentation based on horizontal line profile was computed to these images in localizing the bedridden as region of interest. After that, the biggest blob selection was executed in selecting the blob of bedridden person body. Finally, blob analysis was formulated to the resultant image before boxplot and machine learning approach called decision tree were used to analyze the output features of blob analysis. Based on the results from the boxplot analysis, it seems that centroid-x is the most dominant feature to recognize awakening event successfully as the boxplot represent the centroid-x of awakening event were not overlap with other sleeping activities. The result from machine learning approach is also seem in good agreement with boxplot analysis whereby the modelled decision tree with solely using centroid-x achieve the accuracy of 100%. The second largest accuracy is the perimeter followed by major axis length and area.

Keywords: Bedridden, fall, depth image, machine learning, decision tree

INTRODUCTION

Bedridden is referring to a person who is confined to bed or unable to leave bed due to medical orders, illness or psychological misfortune. There are possibility for bedridden to fall out of bed when left unsupervised which might cause serious injuries (Geer Cheng, 2013). However, 24/7 hour supervision of bedridden by the caregivers might be quite difficult to be done especially when the caregiver is handling a huge number of bedridden patients. Thus, the risk of bedridden to fall when there are no caregivers around might increase. According to (Hamid, 2015), fall might occur among the bedridden person especially elderly which is about 30% of those over 65 years and 40% of those over 80 years. From the total number of falls happen, bedroom can be considered as one of the most common falling location (Lim *et al.*, 2013). This is why an automated bedridden monitoring system is vital to recognize the awakening events of bedridden and further alert the caregivers to instantly give assistance to prevent falls.

Nowadays, there are many technology intervention for monitoring system in healthcare industries. One of technologies that is used for health-related purposes is Microsoft Kinect that was used for recognize human gestures (O. Patsadu, 2012), head detection for fall prevention (Anh Tuan Nghiem, 2012) and other application due to the promising potentials in term of accuracy rate (Kim, 22 February 2012). However, little study has been done in using Kinect to monitor bedridden in fall prevention especially by utilizing the occurrence of awakening event (Choon Kiat Lee, Jonathan Knorn, 2016, Martinez *et al.*, 2013, Monish Parajuli, 2012, Vilas-Boas M, 2013). The awakening event is considered since such event is the high potential event that fall might occur for bedridden person.

Thus, the aims of this study is to evaluate the features from the Kinect-like depth image using box plot analysis as well as machine learning approach called decision tree for detecting the awakening event of bedridden person toward development of an automated system for fall prevention among the bedridden.

RELATED WORKS

There are several works were proposed in developing the automated monitoring system for bedridden person. One of the existing system is called MovinSense (Vilas-Boas M, 2013) that used a single tri-axial accelerometer attached to the patients' chest to monitor bedridden patients. The work in (Martinez *et al.*, 2013) used Kinect to monitor the bedridden by estimating the bed occupancy, body localization, body agitation and sleeping positions from the depth image while the study in (Lee *et al.*, 2015) detected the sleeping posture and movement in obtaining the overall sleeping information. Furthermore, work in (Yun Li, 2014) focused on the detection of patient's bed status using the depth information, the 3D bed edges, bed height and bed chair angle which are estimated from the Kinect-like depth image to monitor bedridden position and status.

There are also several studies focused on bedridden monitoring which is not for detecting or preventing a fall but the proposed systems were designed for preventing the pressure ulcers among the bedridden. Pressure ulcers is caused when the bedridden lying on the same sleeping posture for long periods of time. For example, study in (R. Yousefi, 2011) used pressure mapping system to create a time-stamped and whole-body pressure map while study in (C.C. Hsia, 2009) proposed the Kurtosis and skewness estimation extracted from signal obtained from the cost-effective pressure sensitive mattress in preventing the ulcers. Other than that, work in (Barsocchi, 2013, C.C. Hsia, 2009) used wearable wireless transceivers, support vector machine and K-nearest neighbour methods in order to recognize position of bedridden.

Thus, since there are only a few works focused on fall prevention among the bedridden, the evaluation of feature from Kinect-like depth image for fall prevention system among bedridden person was proposed in this study. This is also due to the Kinect has many advantages such as portable, low-cost, high frame-rate at 30 Hz, fast 3D information, and accurate depth information (Wu, 2011) as well as comparable with other existing 3D motion capture system available in the market which is suitable to be used in this project.

Machine learning especially supervised learning is part of Artificial Intelligence whereby the machine, the computer, will perform tasks with the training provided by human. Training is given by compiling the data that human observed whereby the program will learn and generate the information that will benefit and meaningful to the human (Mohamed, 2017). The crucial part in classifying the data using supervised learning is the feature selection or extraction which is to extract only useful information from the raw data. Machine will use the selected features to do classifying process (Gentleman *et al.*, 2008). The performance of this machine learning can be evaluated by the classifiers' prediction accuracy where the percentage of correct prediction divided by the total number of predictions. Instead of developing the automated system, the machine learning can also be used to analyze the data especially the feature candidate which might significant in determine or predicting the output. There are five type of common supervised learning or classifier which are Naïve Bayes (NB), k-Nearest Neighbor (k-NN), Decision Tree (DT), Support Vector Machine (SVM) and Artificial Neural Network (ANN). However, Decision Tree was used in this study since this machine learning approach can be converted into a set of rules which is easily understandable and interpretable in inferring the analyzed features.

MATERIALS AND METHOD

Data acquisition and collection

In this study, the depth image dataset of 20 subjects performing six sleeping activities including awakening events (See Fig. 1) were established. In this study, both left and right side of the bed were considered in performing the awakening event and awakening event on left side is called PL while awakening in right side is called PR. Fig. 2 shows the recommended experimental setup whereby the Kinect was placed at the centre of the front side of bed with distance of 1.5 metres and at a height of 2.94 metres. The corresponding depth images of the subject are shown in Fig. 3.

Fig. 1 Sleeping activities done by subject: (a) Feotus (P1); (b) Log (P); (c) Yearner (P3); (d) Soldier (P4); (e) Starfish (P5); (f) Awakening Event (PL).

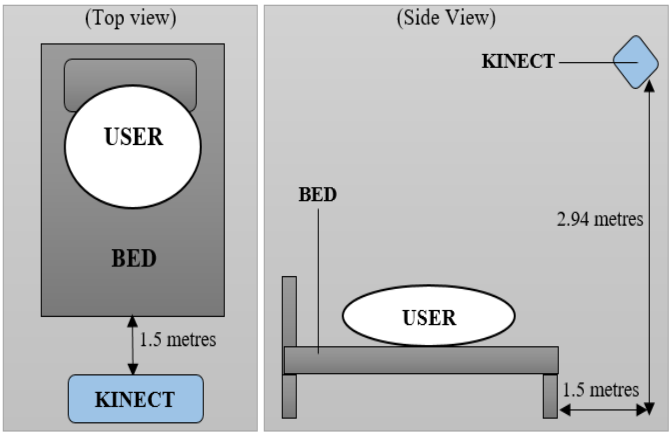


Fig. 2 Experimental setup for data acquisition and collection.

Fig. 3 Data acquisition and collection for sleeping activities.

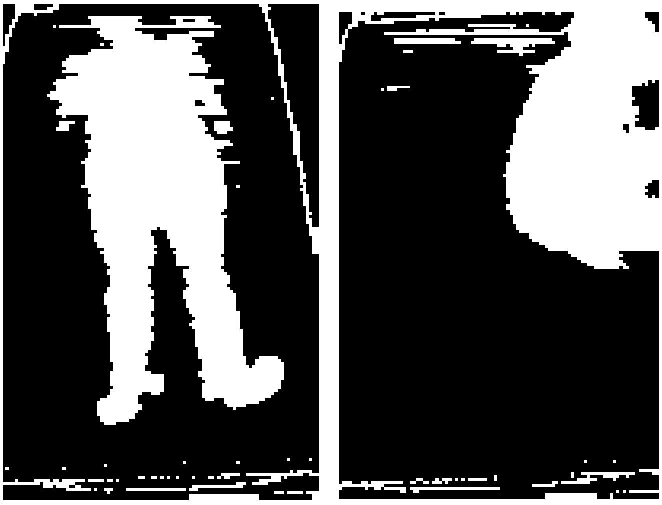
Image segmentation

Before segmentation was computed, one time calibration need to be executed. In this calibration process, the image of empty bed was obtained (See Fig. 4) and the bed region was manually cropped from the depth image. From this process, the cropping coordinates were stored into the system (for the segmentation process) and the horizontal line pixels of the entire line in the cropped region (the empty bed) were collected. After that, the mean of each lines were calculated and stored into the system (for the segmentation process). Then, the collected image from the previous section were cropped using the same coordinates that are stored before and the cropped image was segmented using the following equation:

$$g(x,y) = \begin{cases} 1, & f(x,y) > \mathit{horizontal\ line\ mean} \\ 0, & \mathit{elsewhere} \end{cases} \tag{1}$$

Whereby the horizontal line mean or horizontal line profile was used to determine the threshold value. The depth image of an empty bed was as shown in Fig. 4 while Fig. 5 (a) and (b) shows the image of subject after segmentation for sleeping activities and awakening event.

Fig. 4 Image of an empty bed.

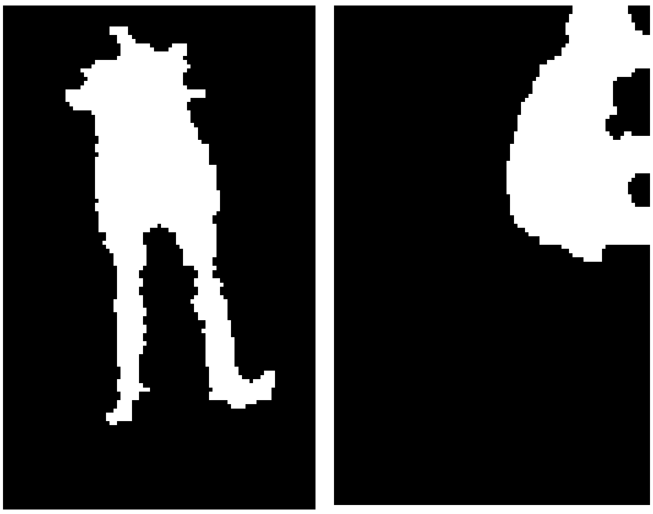


(a) (b)

Fig. 5 Image of subject after segmentation doing sleeping activities: (a) sleeping on bed (P4); (b) awakening event (PL).

Morphological process

After that, the morphological process consists of four times erosion with 'disk' structure element and two times dilation with 'square' structure element were executed to the segmented image in order to remove noise from the image especially the white pixels in the background which can be considered as false detected object pixels. By eroding the image, the background noises including the bed, were removed, leaving only the image of the subject (the object). Next, the image of the subject was dilated twice to ensure the continuity of the image, so that the output image will not have separated pieces of body parts. Fig. 6 (a) and (b) present the segmented image after morphological process:

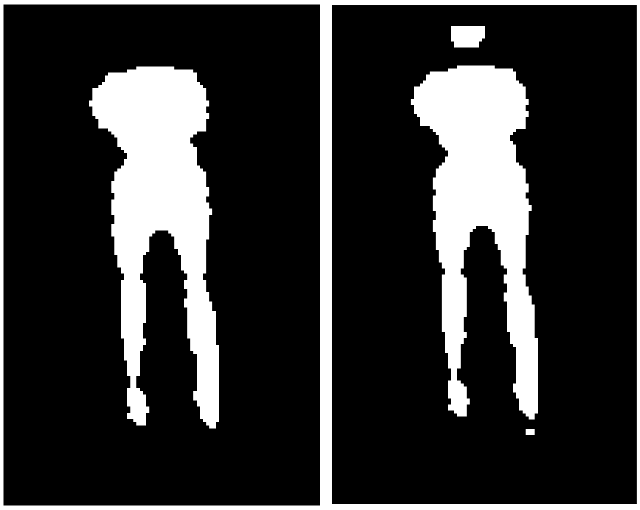


(a) (b)

Fig. 6 Image of subject after morphological process doing sleeping activities: (a) sleeping on bed (P4); (b) awakening event (PL).

Biggest Blob Selections

Although the image has been dilated to ensure its continuity, there were still several images sample that have separated body parts. This problem can be seen in Fig. 7 whereby the image consists of several blobs. As a result, the complexity of the extracted feature will increase if more than one blob exists in the image. Thus, blob selection was done in order to get only the biggest blob and remove other blob in the image. Fig. 7 (b) illustrates the resultant image after the blob selection was formulated to the image in Fig. 7 (a). This function retains the biggest blob and remove other smaller blobs; by assuming the biggest blobs represent the image of subject.



(a) (b)

Fig. 7 Image of subject doing sleeping activity: (a) before biggest blob selection; (b) after biggest blob selection.

Blob and feature analysis

At this stage, blob analysis was computed to evaluate the features from Kinect-like depth image that can represent the awakening event of the 20 subjects. Six features were extracted from the biggest blob which are area (A), perimeter (P), minor axis length (Mi), major axis length (Ma), centroid-x (Cx) and centroid-y (Cy) of the subject's blob. After that, these features are analyzed using two methods: 1) boxplot analysis; and 2) machine approach to find the most significant features that can differentiate between awakening events and other sleeping activities.

Six boxplots were produce to represent the aforementioned six features against the type of sleeping activities including awakening events that was performed by the 20 subjects. The pattern of the boxplot of each figures are analyzed and the most significant features that did not have any overlapping between the awakening events and other sleeping activities are considered to be the best feature to be used for detecting the awakening events of the subjects.

While in machine learning approach, the conventional supervised learning which is decision tree classifier was used to identify the best feature combination in detecting the awakening event. By using decision tree classifier, there are two techniques were used in analyzing several combination features that represent the awakening event which are: 1) analyzing the accuracy produced by several decision tree classifiers which were trained with different feature combination of training data; and 2) observing the rule generated from modelled decision tree classifier in identifying the descriptive power of the features. The k-folder cross validation (k=10) was used in both technique in selecting the managing the training and testing data as well as producing the accuracy of the modelled decision tree.

RESULTS AND DISCUSSION

The results obtained in feature analysis stage based on box plot are presented in Fig. 8-13 that indicate the each features for sleeping activities including awakening events done by 20 subjects.

Box plot technique was used to analyze which features can discriminate the awakening events from other events (other sleeping activities). This is because this technique is simple and suitable for visual representation of large data distribution. Overall, based on the results in Figure 8-13, almost all features were slightly overlapping between each other which might be due to the different body size, height and gender among different subjects. However, it can be seen in Figure 12 that the boxplot of centroid-x that represents the awakening event (the boxplot of PR and PL) were not overlap with other sleeping activities (P1-P5). Thus, this feature can be considered as the excellent feature in representing the awakening events based on boxplot analysis.

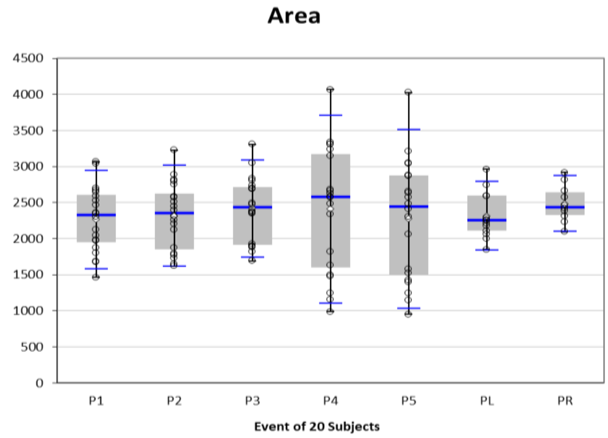


Fig. 8 Value of area for sleeping activities including awakening events.

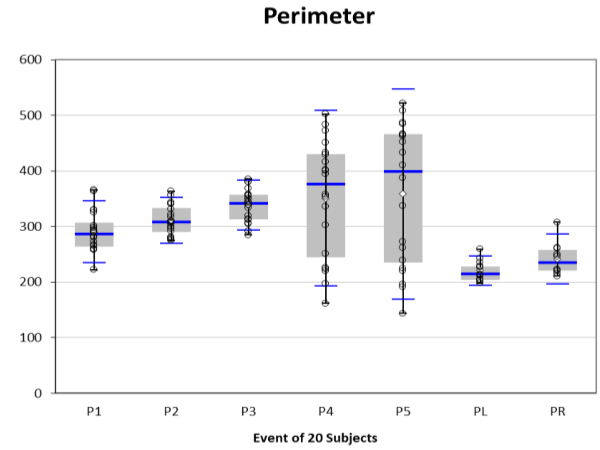


Fig. 9 Value of perimeter for sleeping activities including awakening events

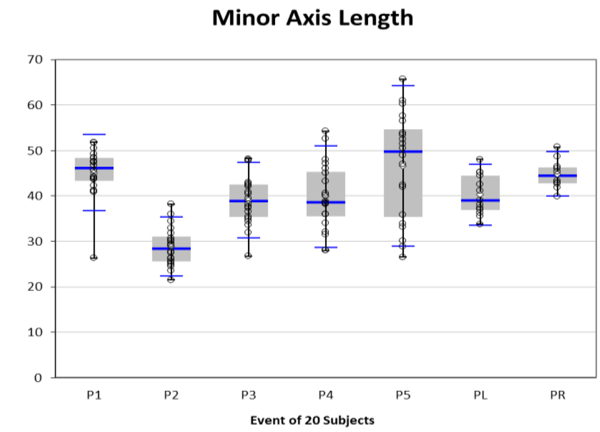


Fig. 10 Value of minor axis length for sleeping activities including awakening events

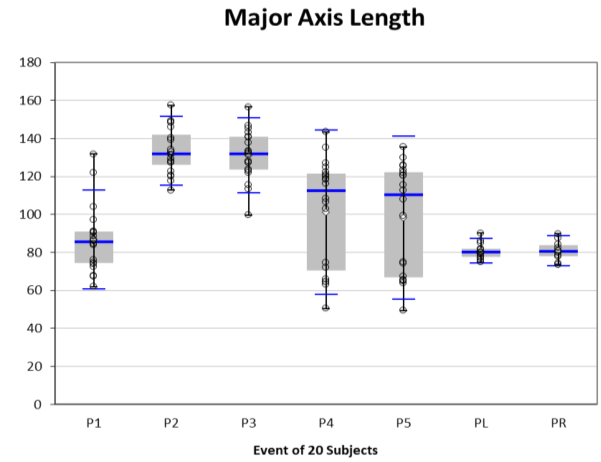


Fig. 11 Value of major axis length for sleeping activities including awakening events.

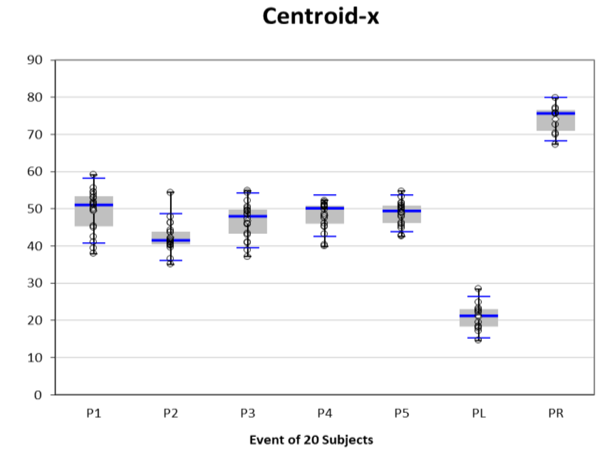


Fig. 12 Value of centroid-x for sleeping activities including awakening events.

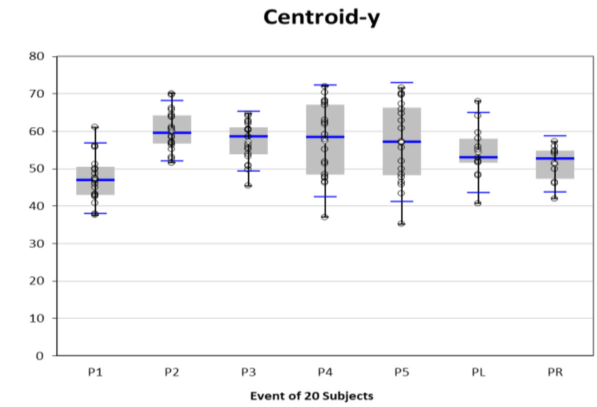


Fig. 13 Value of centroid-y for sleeping activities including awakening events.

Boxplot can be used to observe which feature is appropriate in representing the awakening event in subjective interpretation. However, in providing the objective or quantitative interpretation, the machine learning approach is vital. Table 1-6 show the accuracy of different modelled decision trees which are trained using different features combination. Overall, all tables indicate that the centroid-x (Cx) is the most dominant feature in representing the awakening event as the existing of centroid-x (Cx) in all features combinations produce the modelled decision tree with accuracy of 100%. In contrast, the feature combination without centroid-x will result the accuracy of the modelled decision tree dropped to less than 100% whereby the worst case in the combination of modelled decision tree that was trained solely using Minor Axis Length (Mi) as displayed in Table 2. It also can be highlighted in Table 2 that the modelled decision tree which is solely depend on Centroid-x (Cx) manage to achieve the accuracy of 100% . This might indicate that by using solely centroid-x (Cx) is adequate to establish the awakening event detection system. Moreover, the achievement of excellent result with single feature is preferable in the decision making process since less dimension features will reduce the burden of classifier amd reduce the computational time for both training and test phase.

Table 1 Accuracy of decision tree classifier which is trained using all features.

Features Combination (use all features)						Accuracy (%)
A	P	Mi	Ma	Cx	Cy	100

Table 2 Accuracy of decision tree classifier which is trained using one feature.

Features Combination (remove 5 features)						Accuracy (%)
A						82.5
	P					87.5
		Mi				79.2
			Ma			86.7
				Cx		100
					Cy	80

Table 3 Accuracy of decision tree classifier which is trained using two features combination.

Features Combination (remove 4 features)						Accuracy (%)
A	P					95.8
A		Mi				83.3
A			Ma			85.8
A				Cx		100
A					Cy	83.3
	P	Mi				89.2
	P		Ma			95
	P			Cx		100
	P				Cy	88.3
		Mi	Ma			88.3
		Mi		Cx		100
		Mi			Cy	81.7
			Ma	Cx		100
			Ma		Cy	93.3
				Cx	Cy	100

Table 4 Accuracy of decision tree classifier which is trained using three features combination.

Features Combination (remove 3 features)						Accuracy (%)
			Ma	Cx	Cy	100
		Mi		Cx	Cy	100
		Mi	Ma		Cy	91.7
		Mi	Ma	Cx		100
	P			Cx	Cy	100
	P		Ma		Cy	95.8
	P		Ma	Cx		100
	P	Mi			Cy	89.2
	P	Mi		Cx		100
	P	Mi	Ma			95
A		Mi	Ma			88.3
A	P		Ma			95
A	P	Mi				95.8
A		Mi		Cx		100
A	P			Cx		100
A			Ma	Cx		100
A			Ma		Cy	90.8
A				Cx	Cy	100
A	P				Cy	96.7
A		Mi			Cy	83.3

Table 5 Accuracy of decision tree classifier which is trained using four features combination.

Features Combination (remove 2 features)						Accuracy (%)
		Mi	Ma	Cx	Cy	100
	P		Ma	Cx	Cy	100
	P	Mi		Cx	Cy	100
	P	Mi	Ma		Cy	95.8
	P	Mi	Ma	Cx		100
A			Ma	Cx	Cy	100
A		Mi		Cx	Cy	100
A		Mi	Ma		Cy	93.3
A		Mi	Ma	Cx		100
A	P			Cx	Cy	100
A	P		Ma		Cy	97.5
A	P		Ma	Cx		100
A	P	Mi			Cy	96.7
A	P	Mi		Cx		100
A	P	Mi	Ma			95

Table 6 Accuracy of decision tree classifier which is trained using five features combination.

Features Combination (remove 1 feature)						Accuracy (%)
	P	Mi	Ma	Cx	Cy	100
A		Mi	Ma	Cx	Cy	100
A	P		Ma	Cx	Cy	100
A	P	Mi		Cx	Cy	100
A	P	Mi	Ma		Cy	97.5
A	P	Mi	Ma	Cx		100

Figure 14 presents the rule generated by the modelled decision tree that was trained with combination of all feature whereby the accuracy of the decision tree is 100% as stated in Table 1 for classifying between awakening event (PL|PR) and other sleeping activities (Non-PL|PR). It can be intepreted in Figure 14 that by only utilize the centroid-x (Cx), the decision tree manage to classify between awakening event and other sleeping activities. Thus, it is similar to the previous discussion of Table 2 whereby the centroid-x (Cx) is the most important and dominant in represting the awakening event. Moreover, Figure 15 shows the rule generated by the modelled decision tree if the centroid-x (Cx) was removed from the feature combination to analyzing strength of other features in representing the awakening event. In can be concluded in this figure that Perimeter (P) is the second most dominant followed by Major Axis Length (Ma) and Area (A) in detecting the awakening event. This can be identify by observing the type of feature selected in the 1st and 2nd level of splitting (see Figure 15) whereby the aforementioned type of features are involve. This is due to the nature of decision tree which will select the most dominant feature at the initial level of splitting before continuing identify the next second or third most dominant feature at the higher level of splitting. On the whole, the strength of features other than centroid-x as indicate in Figure 15 is in good agreement with the result in Table 2 whereby the perimeter (P) produce the largest accuracy value after the centroid-x (Cx) followed by Major Axis Length (Ma) and Area (A).

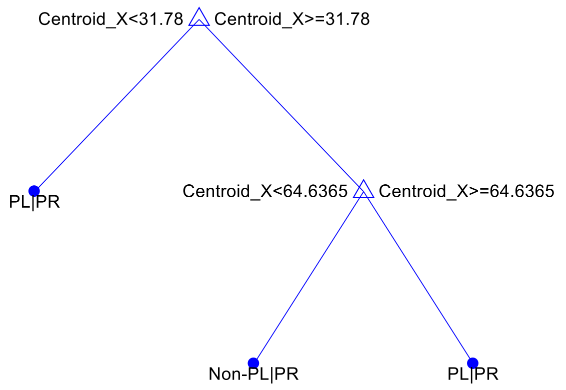


Fig. 14 Rule generated from modelled decision tree classification which is trained using combination of all features.

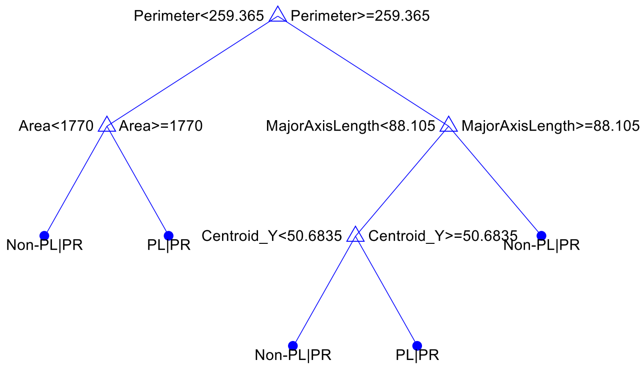


Fig. 15 Rule generated from modelled decision tree classification which is trained using the combination of all features except centroid-x.

CONCLUSION

As a conclusion, features from Kinect-like depth image formulated from blob analysis technique have been analyzed to identify and differentiate between awakenings with other events. Based on the results from the boxplot analysis, it seems that centroid-x is the most dominant feature to recognize awakening event successfully as the boxplot represent the centroid-x of awakening event were not overlap with other sleeping activities. The result from machine learning approach is also seem in good agreement with boxplot analysis whereby the modelled decision tree with solely centroid-x as feature achieve the accuracy of 100%. The second largest accuracy is the perimeter followed by major axis length and area. Therefore, the finding of this study can be used to establish an automated system that can detect a pre-fall (awakening event) which will prevent a fall by alerting the caregivers when awakening event occurs.

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