Non-Invasive Monitoring of People with Disabilities via Motion Detection

Theng B. Lau, Ann C. Ong, and Fernando A. Putra
Swinburne University of Technology Sarawak, Kuching, Malaysia
Email: blau@swinburne.edu.my

***Abstract*—This research developed a prototype to recognize the activities of people with social interaction and communication impairments using two commercial grade infrared motion sensing input devices. The model uses skeletal joints in the form of (x, y, z) coordinates to perform computationally inexpensive and efficient real time indoor monitoring. The prototype works well for a room with the size of 15 ft. by 15 ft. where it can detect two human subjects simultaneously. The prototype promotes non-invasive monitoring, no wearable sensor is required on the person under monitoring and no identifiable face images are stored. The evaluation shows that it is able to recognize the accident-critical activities, self-injurious activities and inactivity with satisfactory recognition and false alarm rates.**

***Index Terms*—activity recognition, human body joints, gesture, accident-critical, self-injurious, inactivity, fall detection, people with disabilities, motion sensor**

I. Introduction

People with social interaction and communication disabilities have three challenging behaviors: 1) destructive behaviours like aggressive, self-Injurious, property destruction, injury to others, throw, push, harmful behaviour with hands and feet; 2) disruptive behaviours like tantrums, loud noise/screaming/crying, running, repetitive noises, talking out, negative comments; 3) interfering and/or irritating behaviours like self-stimulation, repetitive and perseverative speech/questions, argumentative, poor task completion [1]. The key to lock these behaviours is a positive behavioural support which requires a lot of real time care, monitoring and social instruction as appropriate. According to the study by Raja *et al.* [2] on 26 patients with Autism Spectrum Disorders, ASD, 30.8% presented suicidal ideation and 7.7% committed suicide.

For people with social interaction and communication impairments, self-injurious behaviours or activities like head banging (on floors, walls or other surfaces), hand or arm biting, hair pulling, eye gouging, face or head slapping, skin picking, scratching or pinching and forceful head shaking could invite some involuntary injuries that need prevention [3]. The trigger was mainly due to inability to express their thoughts and be understood by others [4]. CALL7 [5] reported a patient was found dead in Colorado Mental Health Institute after overconsumption of drug, also contributed by the lack of real time activity monitoring. Currently, the focus on assistive technology for people with social interaction and communication impairments is mainly on learning (language and social skills) and speech therapy [6]-[9]. As to date, there is still a lack of real time intelligent ICT based tool to monitor, detect, recognize and alert in case of any critical behavior occurrence. The scarcity of the systems for preventing injury for people with multiple disabilities leads this research to source for a good contemporary solution.

II. Background

When we surveyed the systems for preventing injuries among people with disabilities, most of them focus on fall detection. Some of the systems used wearable devices designed mainly for the elderly community with motor skills and capability to operate the devices. As for vision based systems, they required real time video streaming that are computationally expensive and hardware consuming. In general, the disabled people fall frequently and easily, most of the falls cause injury. In some cases, unintentional fall may even bring them to death [10], [11]. Furthermore, people with multiple disabilities have difficulty to communicate with others using comprehensible speech [12]. Recent studies [10], [13], [14], [15] have highlighted a need to develop fall detection system to trigger alarm whenever a person under monitoring fall and need assistance. According to Mubashir *et al.* [11], fall detection can be divided into three categories: wearable device based, ambience sensor based and vision based. Most of the fall detection models detect fall using wearable device i.e. pendant, watch or mobile phone advertised in Alert1, MobileHelp and LifeAlert not designed for people with multiple disabilities [16], [17]. If a person loses consciousness, the devices become useless as the alarm cannot be triggered. Besides, wearable devices required some motor skills and knowledge to use the interfaces [14]. User may feel unpleasant (intrusive) wearing the devices all the time and chooses to discontinue [10], [13]. In some instances, they might forget to put it on [15], [18].

On the other hand, Doulamis *et al.* [19] uses vision based monitoring to detect fall. Zweng *et al.* [14] proposed statistical behavior fall detection which captures the human subject's behavior using multiple cameras. Mastorakis and Makris [15] uses Kinect's infrared sensor

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to detect human fall by measuring the velocity based on the contraction or expansion of the width, height and depth of the 3D bounding box expressed in world coordinate system. Mubashir *et al.* [11] commented that vision based approach in comparison to wearable devices based and ambient based, is certainly the area to look forward to as it deals with intrusion and robustness better. Multi depth motion sensors have been adapted in various low cost and high efficiency vision based monitoring [20], [21]. For instance, fall prevention, post-stroke rehabilitation [22], [23], early warning system for forthcoming health issues of residents in apartments [24], remote health monitoring for patients who suffer from multiple Sclerosis and chronic ailments which require periodic physiotherapy and monitoring [25] and tracking movement in m/second of at-risk children [26]. Most of the activity monitoring models focus on fall detection and neglect other possible threats that occur without a prior fall such as the loss of consciousness while sitting [27].

III. Activity Recognition

Ong, Lau and Bagha [28], we investigated and developed a model on recognizing the user's gesture of falling, seeking help and inactivity. As an improvement to [28] to assist in monitoring people with disabilities, enhanced algorithms to recognize the common activities (observed through people with special needs) were modeled. The activities are categorized by accident-critical i.e. fall, jump, slab, punch, kick, wave hands, climb and run; self-injurious i.e. head-banging, self-hitting, jumping down from a higher location and inactivity i.e. sit, bend, rest and stand still continuously. The activities are recognized by analyzing the movements of joints when performing various gestures, samples of the gesture are shown from Figure 1 to Figure 6. We model activities by utilizing the skeleton height, region of interest (ROI) and movement speed of the joints in three dimensional coordinates (x, y, z). For human subject height measurement, the automated height measurement has an average discrepancy of 4cm when we performed ground truth checking with the human subjects. The discrepancy of not more than 10cm is the requirement for the activity recognition to perform accurately. The maximum height of the ROI is the height of the frame i.e. 480 pixels while the width of the area increases or reduces when different gestures are performed. For instance, ROI centered at the head and shoulder joints is used to detect the head-banging gesture. As for climbing, ROI centered at the foot and ankle joints is used instead. By estimating the movement speed from the current X or Y and previous joints, the model can recognize the more dynamic gestures like punching, slapping, running and kicking.

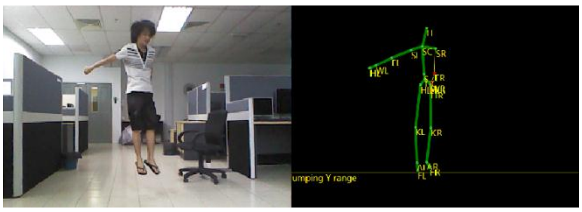

Figure 1. A jumping gesture

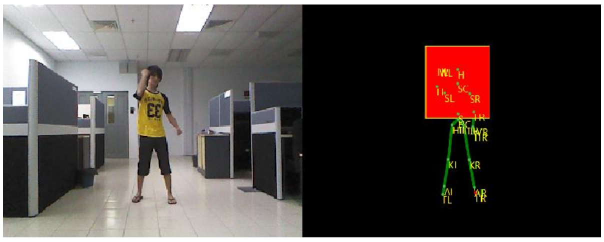

Figure 2. A self-hitting gesture

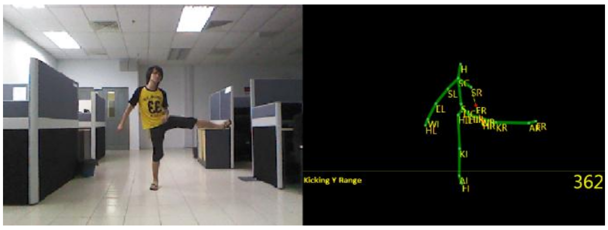

Figure 3. A kicking gesture

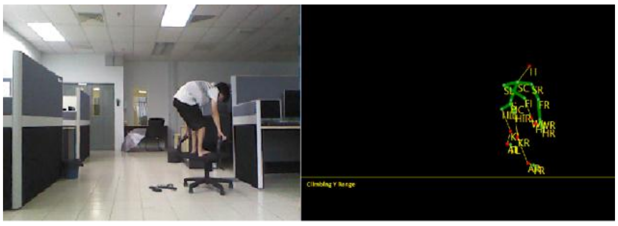

Figure 4. A climbing gesture

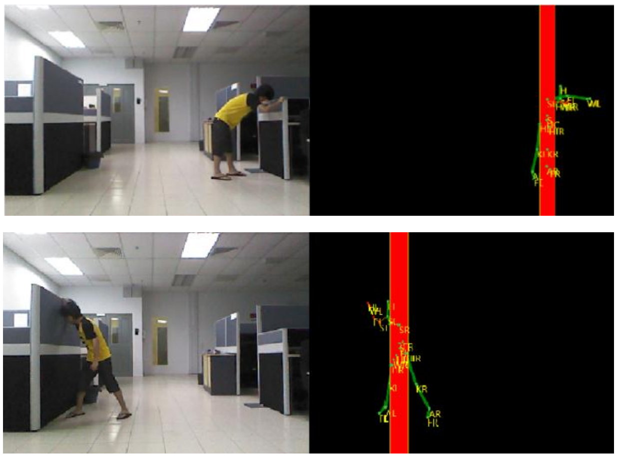

Figure 5. A head-banging gesture

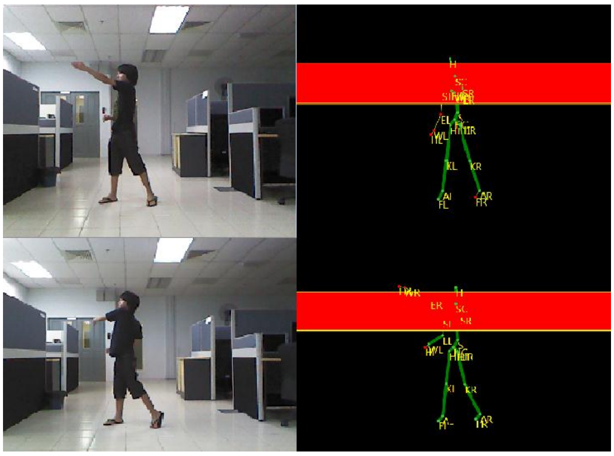

Figure 6. A slapping gesture

IV. PROTOTYPE

We developed a prototype which incorporated the modeled body gesture for injury related gesture recognition. We classified the body gestures into three main category i.e. accident critical, self-injurious and inactivity as the possible activities leading to injury. The conceptual design of our proposed model is illustrated in Figure 7. The human's skeletal and joints are localized using infrared (IR) motion sensor [29]. This sensor uses infrared beam to detect skeletal structure with 20 important joints. An infrared image with human's skeletal and joints representation is produced, these representations are utilized for the activity recognition. They are two infrared (IR) sensors being used, responsible for capturing real time scene and localizing human's skeletal and joints in three dimensional coordinates (x, y, z). Then, the human's skeletal and joints representation is forwarded to activity recognition module for pattern recognition and alert notification. The activity recognition module detects accident-critical activities i.e. fall, jump, slab, punch, kick, wave hands, climb and run; self-injurious activities i.e. head-banging, self-hitting, jumping down from a higher location and inactivity i.e. sit, bend, rest and stand still. Notification module is responsible to pass the alert to guardian through channels like email, Short Messaging System (SMS), Facebook messenger and Google Hangout chat via the available internet connectivity.

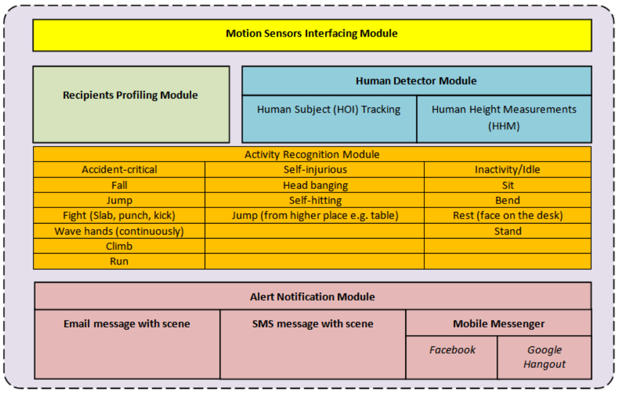

Figure 7. Conceptual Design of IRESY 2.0

The main screen of the prototype, IRESY 2.0 is shown in Figure 8. The real time motion detection sends skeletal images to the detection modules. When any accident-critical activity, self-injurious activity or inactivity is detected, it notifies the caretaker by sending SMS message, email and messenger chat. For the gesture of fall, if the subject under monitoring is recognized to perform a gesture of falling and the status of falling remains for 15 seconds, an alarm is triggered. The delay of 15 seconds is to avoid the model from sending false alarm such as the human subject could be performing an exercise instead of falling. For the gesture of inactivity, if the human subject under monitoring is recognized as in an inactive state for more than 30 seconds, an inactivity alarm is triggered. This could indicate that the subject has lost consciousness or ability to maneuverer. For the gesture of wave hand(s), if a gesture of waving hand(s) continuously (possibly relates to seeking for help) is recognized through the real time skeletal images, the notification module generates and sends a snapshot of the current scene through email, messenger chat (via Google Hangout or Facebook) or message (SMS). A sample of email alert is shown in Figure 9.

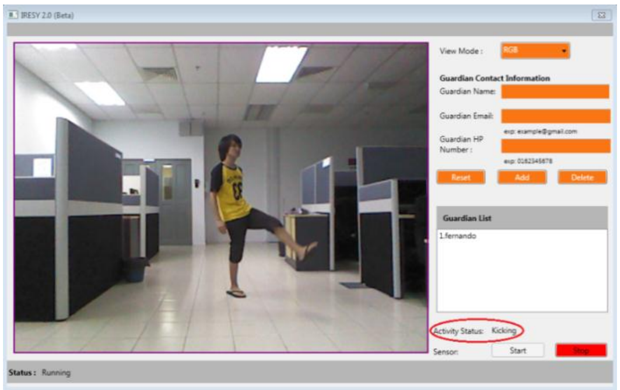

Figure 8. Main interface of IRESY 2.0

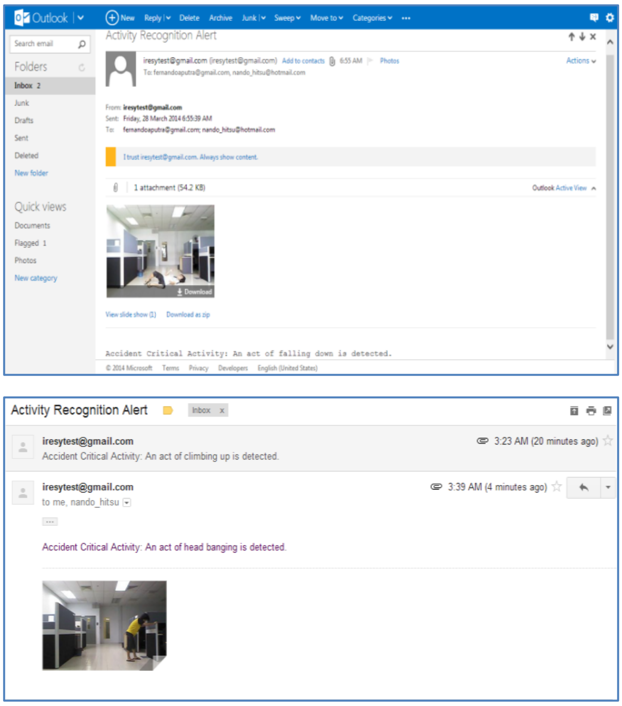

Figure 9. Samples of alert received through email

V. TESTING AND EVALUATION

We invited 20 volunteers to evaluate the efficiency of our prototype in an indoor environment with the area of 15 ft. x 15 ft. fixed with two commercial grade motion sensing input devices. Each volunteer gave his/her consent after explaining to them the requirements (prior to the testing). The volunteers have a mixture of male and female. To maintain anonymity and privacy, their pictures are not published. The evaluation aimed to test the accuracy of the prototype in differentiating the accident-critical activities, self-injurious activities, inactivity from the normal activities. False alarm rate indicates the rates where false recognition of gesture happened throughout the evaluation, for instance when a human subject under monitoring demonstrated an accident-critical gesture of "jump from a higher place", it is recognized as normal activity. Each volunteer was given the specific scenarios to perform various gestures in three categories i.e. accident-critical, self-injurious and inactivity in an indoor environment. TABLE shows the results obtained for accident-critical activities; we obtained an overall of 91.58 % of recognition accuracy. For the recognition of waving hand(s) (to seek help), the volunteers were given three scenarios, 1) Wave while bending on the floor, 2) Wave while sitting on the chair, and 3) Wave while standing which achieved a recognition rate of 100% in all test cases. As for inactivity recognition, we tested on two scenarios, 1) sit/bend still for more than 60 seconds and 2) sit still with the head on the desk for more than 60 seconds, the recognition achieved an average accuracy of 100% in all the test cases.

TABLE I. ACTIVITY RECOGNITION ACCURACY AND FALSE ALARM RATES

Accident-critical Gesture	Recognition (%)	False Alarm (%)
• Jump	95.00	5.00
• Kick	92.50	7.50
• Fight-Punch	90.00	10.00
• Fight-Slap	95.00	5.00
• Fight-Smack	100.00	0.00
• Fight-Clap	70.00	30.00
• Fall	83.33	16.67
• Stand, walk, run	100.00	0.00
• Bend the body	90.00	10.00
• Wave left/right/both hand(s)	100.00	0.00
Average	91.58	8.42
Self-injurious Gesture	**Recognition (%)**	**False Alarm (%)**
• Self-hitting	80.00	20.00
• Head-knocking	90.00	10.00
Average	85.00	15.00
Inactivity Gesture	**Recognition (%)**	**False Alarm (%)**
• Sit/bend (still on a chair)	100.00	0.00
• Sit/bend (still with the head on the desk)	100.00	0.00
Average	100.00	0.00
Overall	91.85	8.15

Each volunteer also demonstrated the gestures of self-hitting, jumping, punching, slapping, clapping, smashing, and kicking in his/her own ways. The gesture of clapping has low recognition accuracy due to the inferred joints detected while performing the activity. The joints were inferred mainly when the right hand's and left hand's joints were not differentiable.

In this evaluation, the overall recognition rate is 91.85%, it indicates the potential of the proposed prototype to be utilized as a non-invasive means for activity monitoring.

VI. CONCLUSION AND FUTURE WORKS

This paper proposed a low cost real time activity recognition prototype that recognizes human body joints from two commercial-grade motion sensing input devices. The proposed system is non-invasive to person under monitoring. The guardian(s) can receive real time alert and snapshot through chat, short message and email when activity that shows accident-critical, self-injurious or inactivity is detected. Overall, the prototype achieved a recognition accuracy of 91.85% with a low false alarm rate of 8.15%. The limitation of this prototype is motion sensing devices lost tracking of the human subject when he/she is blocked by small-sized furniture such as a desk or small cabinet in an indoor environment. We intend to study the possibilities and ways to improve the activity recognition by adding in voice and sound recognition. On the other hand, more accident-critical and self-injurious gestures are to be investigated in future.

The prototype can be embedded into intelligent environment for monitoring people with disabilities living in it. It can be enhanced to recognize more accident-critical and self-injurious activities, and inactivity to prevent injury among people with disabilities. Another potential of the model is incorporating it into rehabilitation of people with disabilities by recognizing their actions and give appropriate responses during the rehabilitation sessions. It also has the potential to be enhanced for monitoring elderly people living alone.

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REFERENCES

[1] C. Thorsen. (2010). Positive behavioral supports and students with autism. *Autism Spectrum Disorder Speaker Series*. [Online]. Available: http://www.indstate.edu/blumberg/docs/claire-thorsen-positive-behavioral-supports.pdf

[2] M. Raja, A. Azzoni, and A. Frustaci, "Autism Spectrum Disorders and suicidality," *Clinical Practice and Epidemiology in Mental Health*, vol. 7, pp. 97-105, 2011.

[3] The National Autistic Society. (2013). Self-injurious behavior. [Online]. Available: http://www.autism.org.uk/living-with-autism/understanding-behaviour/challenging-behaviour/self-injurious-behaviour.aspx

[4] V. Mandasari, "Learning social skills with 2D animated social stories for children with autism spectrum disorders," Dissertation for Masters of Science by Research, Swinburne University of Technology Sarawak, 2012.

[5] CALL7. (2011). Audit: State hospitals failed to monitor patient meds. *The Denver Channel*. [Online]. Available: http://www.thedenverchannel.com/news/audit-state-hospitals-failed-to-monitor-patient-meds

[6] D. Parker and D. Kamps, "Effects of task analysis and self-monitoring for children with Autism in multiple social settings," *Focus on Autism and Other Developmental Disabilities*, vol. 26, no. 3, pp. 131-142, 2011.

[7] V. Gaylord, M. Quinn, J. McComas, and C. Lehr, "Feature issue on fostering success in school and beyond for students with emotional/behavioral disorders," *Impact*, vol. 18, no. 2, pp. 1-40, 2005.

[8] Tobii. (2013). Assistive technology products. [Online]. Available: http://www.tobii.com/assistive-technology/global/products/

[9] Autism Speaks. (2013). Assistive technology. [Online]. Available: http://www.autismspeaks.org/family-services/resource-library/assistive-technology

[10] S. Wang, S. Zabir, and B. Leibe, "Lying pose recognition for elderly fall detection," in *Proc. Robotics: Science and Systems*, Los Angeles, 2011, pp. 345-353.

[11] M. Mubashir, L. Shao, and L. Seed, "A survey on fall detection: Principles and approaches," *Neurocomputing*, vol. 100, pp. 144-152, 2012.

[12] C. A. Ong and B. T. Lau, "A facial expression mediated natural user interface communication model for children with motor impairments," in *Assistive Technologies, Disability Informatics and Computer Access for Motor Limitations*, G. Kouroupetroglou, Ed. IGI Global Publishing, 2013.

[13] E. Auvinet, F. Multon, A. Saint-Arnaud, J. Rousseau, and J. Meunier, "Fall detection with multiple cameras: An occlusion-resistant method based on 3-D silhouette vertical distribution," *IEEE Transactions on Information Technology in Biomedicine*, vol. 15, no. 2, pp. 290-300, 2011.

[14] A. Zweng, S. Zambanini, and M. Kampel, "Introducing a statistical behaviour model into camera-based fall detection," in *Proc. 6th International Conference on Advances in Visual Computing*, 2010, pp. 163-172.

[15] G. Mastorakis and D. Makris, "Fall detection system using Kinect's infrared sensor," *Journal of Real-Time Image Processing*, pp. 1-12, 2012.

[16] J. Tomkun and B. Nguyen, "Design of a fall detection and prevention system for the elderly," BEng Dissertation, McMaster University, 2010.

[17] A. Lombardi, M. Ferri, G. Rescio, M. Grassi, and P. Malcovati, "Wearable wireless accelerometer with embedded fall-detection logic for multi-sensor ambient assisted living applications," *IEEE Sensors*, pp. 1967-1970, 2009.

[18] V. Q. Viet, G. Lee, and D. Choi, "Fall detection based on movement and smart phone technology", in *Proc. International Conference on Computing and Communication Technologies*, 2012, pp. 1-4.

[19] A. Doulamis, N. Doulamis, I. Kalisperakis, and C. Stentoumis, "A real-time single-camera approach for automatic fall detection," *ISPRS Commission V, Close Range Image measurements Techniques*, vol. XXXVIII, pp. 207-212, 2010.

[20] Z. Zhang, "Microsoft Kinect sensor and its effect," *IEEE Multimedia*, vol. 19, no. 2, pp. 4-10, 2012.

[21] E. E. Stone and M. Skubic, "Evaluation of an inexpensive depth camera for passive In-Home fall risk assessment", in *Proc. 5th International ICST Conference on Pervasive Computing Technologies for Healthcare*, 2011, pp. 71-77.

[22] B. Lange, C. Y. Chang, E. Suma, B. Newman, A. S. Rizzo, and M. Bolas, "Development and evaluation of low cost game-based balance rehabilitation tool using the Microsoft Kinect sensor," in *Proc. Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2011, pp. 1831-834.

[23] S. Saini, D. R. A. Rambli, S. Sulaiman, M. N. Zakaria, and S. R. Mohd Shukri, "A low-cost game framework for a home-based stroke rehabilitation system," in *Proc. International Conference on Computer and Information Science*, 2012, pp. 55-60.

[24] Cognizant, "The future of remote health monitoring with Kinect," *Cognizant Technology Alliance*, 2012.

[25] J. Keene. (2011). Kinect aids in improving mobility and rehabilitating stroke patients. *The Verge*. [Online]. Available: http://www.theverge.com/2011/12/20/2648441/kinect-medical-use-mobility-rehab

[26] R. Sivalingam, *et al.*, "A multi-sensor visual tracking system for behavior monitoring of at-risk children," in *Proc. ICRA*, 2012, pp. 1345-1350.

[27] G. Ward, "Fall detectors: A review of the literature," *Journal of Assistive Technologies*, vol. 6, no. 3, pp. 202-215, 2012.

[28] C. A. Ong, B. T. Lau, and H. Bagha, "An injury recognition model using single rotatable infrared sensor," in *Proc. the Second International Conference on E-Technologies and Networks for Development*, 2013, pp. 196-201.

[29] Microsoft. (2013). Kinect for Windows. [Online]. Available: http://www.microsoft.com/en-us/kinectforwindows/

Lau Bee Theng is a senior lecturer and ICT program coordinator at Faculty of Engineering, Computing and Science, Swinburne University of Technology Sarawak. Her research interest is mainly on assistive technologies utilizing ICT for the special people. She has published more than 60 articles in peer reviewed journals, book chapters and conference papers. She has successfully supervised various postgraduate students to completion and coordinated a few research projects on assistive technologies for special children, injury recognition and activity monitoring using multi depth sensors, wireless and Bluetooth devices, brain interfaced human computer interaction.