DEVELOPMENT OF A HUMAN FALL DETECTION SYSTEM BASED ON DEPTH MAPS

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ABSTRACT

Assistive care related products are increasingly in demand with the recent developments in health sector associated technologies. There are several studies concerned in improving and eliminating barriers in providing quality health care services to all people, especially elderly who live alone and those who cannot move from their home for various reasons such as disable, overweight. Among them, human fall detection systems play an important role in our daily life, because fall is the main obstacle for elderly people to live independently and it is also a major health concern due to aging population. The three basic approaches used to develop human fall detection systems include some sort of wearable devices, ambient based devices or non-invasive vision based devices using live cameras. Most of such systems are either based on wearable or ambient sensor which is very often rejected by users due to the high false alarm and difficulties in carrying them during their daily life activities. Thus, this study proposes a non-invasive human fall detection system based on the height, velocity, statistical analysis, fall risk factors and position of the subject using depth information from Microsoft Kinect sensor. Classification of human fall from other activities of daily life is accomplished using height and velocity of the subject extracted from the depth information after considering the fall risk level of the user. Acceleration and activity detection are also employed if velocity and height fail to classify the activity. Finally position of the subject is identified for fall confirmation or statistical analysis is conducted to verify the fall event. From the experimental results, the proposed system was able to achieve an average accuracy of 98.3% with sensitivity of 100% and specificity of 97.7%. The proposed system accurately distinguished all the fall events from other activities of daily life.

ABSTRAK

Produk-produk berkaitan bantuan penjagaan semakin diminati ramai dengan perkembangan terkini dalam sektor teknologi berkaitan dengan kesihatan. Terdapat beberapa kajian yang berkaitan untuk meningkatkan dan menghapuskan halangan dalam menyediakan perkhidmatan penjagaan berkualiti kepada semua orang, terutamanya warga tua yang hidup berseorangan dan orang yang tidak boleh bergerak dari rumah mereka kerana atas pelbagai sebab seperti lumpuh, berat badan berlebihan. Diantaranya, sistem pengesanan orang jatuh memainkan peranan penting dalam kehidupan seharian kita, kerana jatuh adalah halangan utama bagi orang tua untuk hidup secara bebas dan ia juga merupakan masalah kesihatan utama bagi penduduk yang semakin tua. Tiga pendekatan asas digunakan untuk membangunkan sistem pengesanan orang jatuh termasuk beberapa jenis peranti yang boleh dipakai, peranti berasaskan ambien atau peranti berasaskan penglihatan tanpa invasif menggunakan kamera secara langsung. Kebanyakan sistem sedemikian sama ada berdasarkan kepada sensor yang boleh dipakai atau ambien sering ditolak oleh pengguna disebabkan oleh nisbah penggeraan palsu yang tinggi dan kesukaran untuk membawa alat tersebut dalam aktiviti harian mereka. Oleh itu, kajian ini mencadangkan sistem pengesanan orang jatuh bukan invasif berdasarkan ketinggian, halaju, analisis statistik, faktor risiko jatuh dan kedudukan subjek menggunakan maklumat mendalam dari sensor *Microsoft Kinect*. Pengkelasan orang jatuh dari aktiviti lain dalam kehidupan harian dapat dicapai dengan menggunakan ketinggian dan halaju subjek yang diekstrak dari maklumat mendalam setelah mempertimbangkan tahap risiko jatuh pengguna. Pecutan dan pengesanan aktiviti juga digunakan jika halaju dan ketinggian gagal untuk mengelaskan aktiviti. Akhirnya kedudukan subjek dapat dikenal pasti bagi pengesahan jatuh atau menjalankan analisis statistik untuk mengesahkan kejadian jatuh. Dari hasil percubaan, sistem yang dicadangkan dapat mencapai 98.3% purata ketepatan dengan 100% kepekaan dan 97.7% kekhususan. Sistem yang dicadangkan dapat membezakan dengan tepat semua kejadian kejatuhan dari aktiviti lain dalam kehidupan seharian.

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LIST OF ABREVIATIONS

3D	-	Three Dimension
API	-	Application Program Interface
DoG	-	Determinants of Gait
D	-	Distance travelled for irregular movements
H	-	Height of joint or distance from floor to the given joint
HMM	-	Hidden Markov Model
IR	-	Infrared
LED	-	Light Emitting Diode
Nm	-	Nanometer
OS	-	Operating Systems
RBG	-	Red Green Blue
s	-	Standard Deviation
SDK	-	Software Development Kit
SE	-	Standard Error
USB	-	Universal Serial Hub
VGA	-	Video Graphics Array
x	-	x-axis coordinates value of any joint
y	-	y-axis coordinates value of any joint
z	-	z-axis coordinates value of any joint

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CHAPTER 1

INTRODUCTION

This chapter gives a general background of the investigated problems in the proposed research topic. The motivations for the research being conducted were briefly explained. The objectives and the scopes of the study are also discussed along with the significance of this research.

1.1 Background Study

Assistive technology or adaptive technology is an emerging research area since daily living assistance are very often needed for many people in today's aging populations including disabled, overweight, obese and elderly people. The main purpose of assistive technology is to provide better living and health care to those in need, especially elderly people who live alone. It is mainly aimed at allowing them to live independently in their own home as long as possible, without having to change their life style.

In order, to provide better living for them, it is important to have continuous human monitoring systems in their home to inform the health care representatives of any emergency attendance. Among such monitoring systems, fall detection systems are increasing in interest since statistics (Baker & Harvey, 1985; Griffiths, Rooney, & Brock, 2005) has shown that fall is the main cause of injury related death for seniors aged 79 (Kannus *et al.*, 2005; Stevens *et al.*, 2006) or above and it is the second common source of injury related (unintentional) death for all ages (A. Bourke, O'brien, & Lyons, 2007; Kangas *et al.*, 2008). Furthermore, fall is the biggest threat among all other incidents to elderly and those people who are in need of support (Almeida, Zhang, & Liu, 2007; Gostynski, 1990; Gurley *et al.*, 1996; Lin, Chiou, & Cohen, 1996;

C. J. Lord & Colvin, 1991; S. R. Lord *et al.*, 2007; Sadigh *et al.*, 2004; Salvà *et al.*, 2004; Stevens *et al.*, 2006; Teasell *et al.*, 2002; Tinetti & Williams, 1997). Accordingly, fall can have severe consequences for elderly people, especially if not attended in a short period of time (Shany *et al.*, 2012). Similarly, unintentional human fall represents the main source of morbidity and mortality among elderly (Harrington *et al.*, 2010).

Hence, accurate and autonomous human fall detection systems are very important to support the elderly people to live independently. Since it had been proved that the medical consequences of a fall are highly dependent on the response and rescue time of the medical staff (Mubashir, Shao, & Seed, 2013), which is, in fact, only possible with an accurate and reliable fall detection systems that can provide fall alerts. Such systems are also vitally important, since there may be a case where someone losses consciousness or are unable to call for help after a fall event.

Therefore, highly accurate fall detection systems can significantly improve the living of elderly people and enhance the general health care services too. There has been plenty of researches conducted in this area to develop systems and algorithms for enhancing the functional ability of the elderly and patients (Mubashir *et al.*, 2013). This in fact, led to the improvement in the technologies used to make such systems and thus enhanced the detection ratio to make such systems adaptable and acceptable. The confidential levels of such systems are also increased, leading to reduction in labour cost in terms of presence of medical staff at all the times looking after the elderly people. This implies that an accurate human fall detection system could reduce the number or the need of medical staffs looking after the elderly people.

Recent researches conducted on human fall monitoring approaches for elderly people was categorized into five classes (Arshad *et al.*, 2014). These classes (wearable sensor based, wireless based, ambiance sensor based, vision and floor sensor/electric field sensor based approaches) distinguish, the different fall detection methods employed. This categorization of fall detections methods also reflects the characteristics of the movement that leads to fall. Therefore, it is also important to recognize those characteristics of movement in order to understand the existing algorithms used to detect falls and also to device new algorithms to enhance the performance of such systems.

The various methods that has been used to detect human fall such as using a camera to identify a human fall posture or using various sensors to detect fall, shares some common features. Even though different sensors and approaches are used to identify a fall event, from the analysis, the five categories of fall detection methods was re-divided into three main approaches (Luo & Hu, 2004). These three categories are further divided into different sections depending on the sensor and algorithm used to distinguish different detection methods. The three basic approaches are wearable based device, camera based systems and ambience based devices (Luo & Hu, 2004; Mubashir *et al.*, 2013; Yu, 2008) as shown in Figure 1.1.

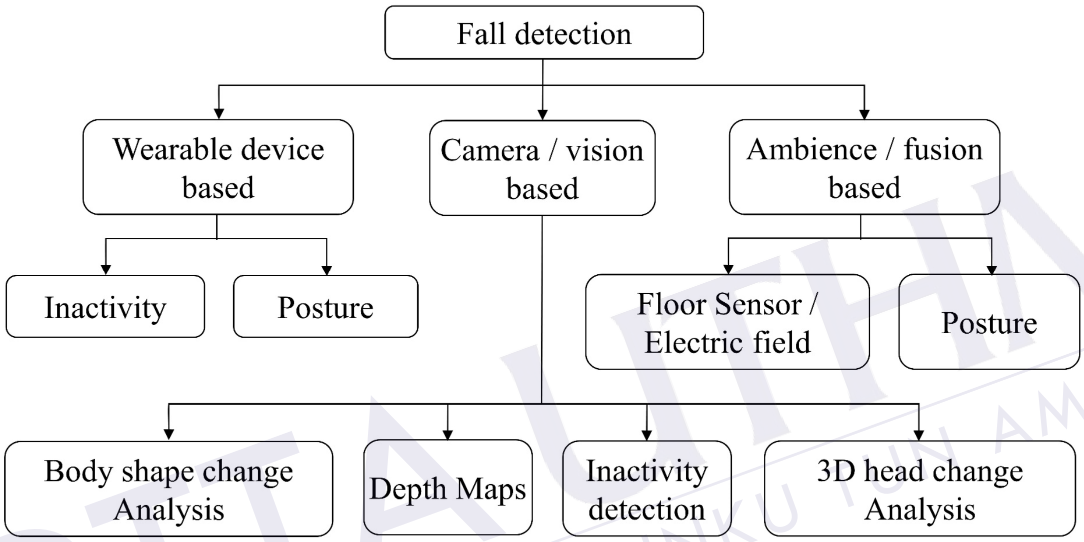

Figure 1.1: Hierarchy of fall detection methods

As shown in Figure 1.1, wearable based device is further divided into two sub-categories based on the fall detection methods used. They are inactivity (motion based) and posture based approaches. Similarly, ambient / fusion based devices are divided into two types; those that used floor sensors or electric field and those that used posture based sensors to detect fall. Camera or vision based approach is divided into four different sub-categories.

Wearable based devices use accelerometers and gyroscopes embedded into garments or any wearing gadgets such as belts, wrist watches, necklace or jacks. The basic concept used to classify human fall is either identifying the posture or through activity/inactivity detection. Ambient/fusion based devices is a type of non-invasive and non-vision based approach. It either use the concept of posture identification through various sensors or uses floor vibration or electric sensors to detect the subject hitting the sensor. On the other hand, vision based (non-invasive) approach uses live cameras or multiples of such cameras to accurately detect human falls through utilizing the analytical and machine learning methods based on a computer vision model. They utilized various approaches to classify human fall including the changes in body shape between frames, activity/inactivity detection of the subject, three-dimensional (3D) analysis of the subject using more than one camera and generating a depth map of the scene with the help of depth sensors. Except the depth sensor based method, the other types in vision based approaches use RGB (Red Green Blue) cameras and therefore they are subject to rejection from user's due to privacy concerns. They are also rejected due to the high cost of the systems, installation and camera calibration issues. A depth image based approach could solve the issues arising from video based systems. Studies representing this approach can also be divided into three types reflecting the approach used. The first category represents those works that employed joint measurements or used human joint movements from depth information to detect fall. The second category includes the works that depended only on depth data with any supervised and unsupervised machine learning to classify human fall from other activities of daily life and the third category includes studies that make use of wearable devices along with the depth sensor. The proposed algorithm is only based on the depth image and uses a statistical model with joint measurement to generate potential fall alert and to classify human fall from other activities of daily life.

1.2 Problem Statement

Accurate human fall detection devices are highly demanding, because it is helpful in changing the life of elderly people and patients with special needs. Among such devices, wearable products with embedded sensors and non-wearable ambient based devices are very cheap and are readily available. However, due to the high false alarm ratio and wearing difficulties (difficulties in carrying them during their daily life activities), it is very often rejected by the users. On the other hand, non-wearable devices such as floor sensor based products also generates lots of false alarms by triggering normal daily activities or sensing the pressure of any objects as human fall. As far as video based solutions are concerned they are accurate than the other two approaches, but it possesses its own drawbacks such as the high cost of the systems, time required for installation and camera calibration are common issues. Additionally, these systems require adequate lighting for accurate human extraction. Furthermore, the lack of depth information used in such systems also leads to generation of unnecessary false alarm. At the same time, sunlight interferences and not preserving the privacy of users are the major concern with video based systems.

1. A depth image based approach could solve the issues arising from video based systems, therefore this study addresses to the concerns arising from such systems. Most of the available depth map based systems are not fully non-invasive to cater the requirements. Some of the studies, still make use of wearable accelerometers or other such devices to identify any potential fall activity. The depth images were simply used to confirm the fall event rather than fully utilizing capabilities of the depth sensor. While others that used only depth images, were dependent on the skeleton data or extracted human joint measurements and does not fully take care of the response time and degradation of person segmentation due to obstacles. Some of them use machine learning which increases the computational costs and the complexity of the fall detection algorithm. The performance of such systems is also subject to the processing time required, processing resources consumed and the response time of the internal potential fall alert mechanism to start the machine learning classification.
2. Furthermore, they use a single fixed procedure to detect human fall event (a single algorithm to detect fall irrespective of the user and the environment), while the nature of the fall, the chances of falls and the consequences of falls will differ from people to people. It also differs depending on the environment such as hospital setting, community setting or nursing homes. The differences of nature of falls and other characteristics of daily activities are due to age, disease or from physical weakness. The available fall detection systems do not address to these issues, rather the issues were combined, and a single solution is proposed which may show an accurate detection ratio for some cases and for other cases it may not.
3. Apart from that, some of the daily life activities possesses similar patterns of unintentional human fall such lying on floor from standing posture. Therefore, it is also important to study the characteristics of all the daily life activities, especially those activities that are similar to unintentional human fall, in order to identify any specific dissimilarity or distinguishing features between them.

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