Human Motion Assistance using Walking-aid Robot and Wearable Sensors

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Abstract: An omni-directional walking-aid robot is developed for the elderly in this study. A motion control strategy of walking-aid robot based on observing human status by wearable sensors is proposed. During normal walking, the robot is controlled by a conventional admittance control scheme. When the tendency of a fall is detected, the robot will immediately react to prevent the user from falling down. The distance between the human Centre of Pressure (COP) and the midpoint of two human feet is assumed to be a significant feature to detecting the fall events. Dubois possibility theory is applied to describe the membership function of 'normal walking' state. A threshold based fall detection approach is obtained from online evaluation of the walking status. Finally, experiments demonstrate the validity of the proposed strategy.

1 INTRODUCTION

The elderly people population is rapidly increasing in developing and developed countries. The increase of human average lifespan escalated the need for elderly-care technologies (Alwan 2008). This increase along with a shortage of skilled caregivers presents an opportunity for robotic applications to address some of the disparities in elderly patient care. In addition, as many elderly and handicapped people suffer from lower extremity deceases, increasing demand for walking aid devices has increased. Robotic applications such as walking-aid robots to assist the elderly in daily activities and to help the elderly regain independence and an increased quality of life will play an important role in the rehabilitative care systems of increasingly aging societies (Jonsson, 2001) and (Mohammed, 2012).

The current walking-aid robot systems proposed so far may be classified into two groups according to mobility factor, i.e., the system moving on the ground according to the motion of the subjects and the system giving effects of walking to the subjects (Lee et al. 2004). The former system is active-type walker (Dubowsky, 2000) and (Hirata, 2003) which is driven by servo motor. The latter corresponds to a system driven by servo brakes and is passive-type walker (Rentschler, 2003) and (Hirata, 2004).

Most of current walking-aid robots only consider the motion control when user is in the normal walking states (Huang, 2008) and (Wakita, 2012), but did not discuss the motion control when user is in abnormal gait situation such as falling down. Falling down is a major cause of fatal injury especially for elderly and may create a serious obstruction for independent living (Griffiths, 2008). The development of walkers should also be based on improving the ability of interaction based on the data from the environment and especially the user to develop monitoring systems especially for fall detection and fall prevention.

Force control techniques including impedance and admittance control methods are widely used in walking-aid robot motion control because they enable user-friendly Human-Robot-Interfaces (HRI) that transform interaction forces from the user to the desired robot motion velocity. Whereas it is difficult to identify emergency cases (e.g. stumbling or slipping) by only using force measurement, and impractical to detect accurate phases of gait training without human body status, intelligent technologies such as wearable sensors and model based estimation approaches allow the realization of suitable motion control to correctly respond to emergency cases and gait training phases. Therefore wearable sensors are used to detected human body status in this paper.

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Wearable device based fall detection method mainly relies on various sensors to detect the motion and location of the body of the user (Mubashir, 2013). To analyse the output of a waist accelerometer, researchers use variance and average, kurtosis and skewness statistics to realize eight kinds of activities such as walking, climbing, running, standing, sitting, and lying prone (Baek, 2004). Masaki (Masaki, 2002) classified the output of waist accelerometers during human climbing motion using fractal analysis method based on a wavelet transform process. Wang (Wang, 2007) obtained data from a 3-axis waist accelerometer, then used 33 different time-domain characteristics to classify the five different types of gaits characteristic of walking on flat ground, uphill, downhill, upstairs and downstairs. In this paper, the force sensors are used to ensure motion control while the wearable sensors are used to detect user's gait through fall classification into three fall gestures.

First, the walking-aid robot and its motion control algorithm are introduced. The framework of the fall detection system based on observing human status by wearable sensors is presented in section 3. Having such data, the test results of proposed algorithm are shown in chapter 4. The conclusions would be the last part of this article.

2 WALKING-AID ROBOT

The prototype of an omni-directional walking-aid robot proposed in our previous work (Ye 2012) is illustrated in Fig. 1. The robot consists of an omni-directional base, a support frame, a motion controller and a battery system.

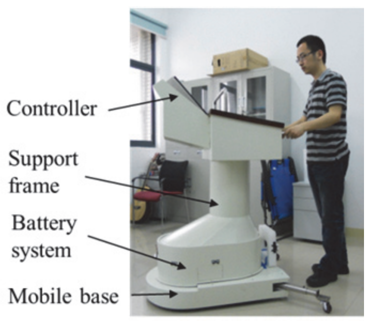

Figure 1: Omni-directional walking-aid robot.

The omni-directional mobile base comprises three commercial Sweden wheels and actuators. Several passive casters are also mounted on the base to widen the support area so as to enhance the stability. Coordinate systems are depicted in Fig. 2. System {0} is the reference coordinate system and {1} is a local system fixed to the robot. Three one-dimensional force sensors are used to measure the interaction forces between the robot and its operator. Both the forward and lateral forces can be obtained, as well as the exerted rotation torque.

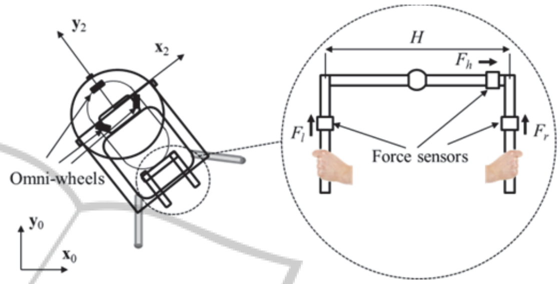

Figure 2: Robot coordinate system (top view) and measurement of interaction forces.

By using the force sensor array, the measured interaction force vector represented in {2} is denoted by $\mathbf{f}_I^2$ which can be calculated from the measured forward and lateral forces. During normal walking, a conventional admittance control is assumed to generate a comfortable human-robot interaction (HRI). The control algorithm is then given by

$$\mathbf{M} \cdot \dot{\mathbf{v}}_R^2 + \mathbf{B} \cdot \mathbf{v}_R^2 = \mathbf{f}_I^2 \qquad (1)$$

where $\mathbf{v}_R^2$ is the robot velocity vector in system {2}. $\mathbf{M} = diag\left(M_x, M_y, M_z\right)$ is the virtual mass parameter matrix and $\mathbf{B} = diag\left(B_x, B_y, B_z\right)$ is the virtual damping parameter matrix.

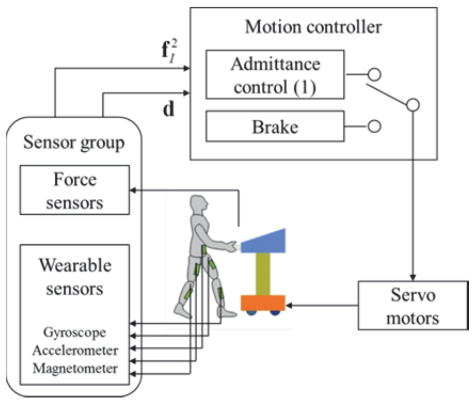

Figure 3: The motion control block diagram of the system.

There are many possible walking modes during the operation of the walking-aid robot. In this paper, we divided all possible human walking states into two modes, ‘normal walking’ and ‘emergency’. During ‘normal walking’ mode, the admittance control strategy (1) is assumed. Wearable sensors are used to detect the occurrence of ‘emergency’ including stumbling or slippage. If an emergent state is detected, the walking-aid robot is quickly braked to prevent the operator from falling down. The whole control architecture is depicted by Fig. 3. The fall detection approach is illustrated in the following sections.

3 FALL DETECTION METHOD

3.1 Wearable Sensors

A wearable sensor unit consists of a tri-axial magnetometer, a tri-axial accelerometer and a tri-axial gyroscope for measuring the acceleration and the angular velocity along three orthogonal axes simultaneously. All sensor units were checked on a mechanical turntable to establish offset values for sensor data in addition to obtaining inclination relationships of the measured values.

The wearable sensor units are placed on five body segments, including both shanks, both thighs and waist (see Fig. 4).

Figure 4: Wearable gait recognition sensor units.

3.2 Gait Recognition

Firstly, several coordinate systems are defined to fulfil the gait recognition (see Fig. 5). System {1} is the human reference coordinate system which is fixed at the waist level with the z-axis pointing to the ground and the x-axis to the magnetic north direction. The direction of y-axis of system {1} is obtained following the right hand rule. For each joint point, there are two coordinate systems. For example, system $\{R_2\}$ is a coordinate system that is fixed on point R_2 and has the same orientation as system {1}. System $\{sR_2\}$ is a sensor coordinate system that is fixed on point R_2 with same orientation as a local sensor coordinate system $\{s\}$. The z-axis is perpendicular to the sensor surface and the x-axis points upward and is parallel to the sensor surface. For any other joint point P, similar coordinate systems $\{P\}$ and $\{sP\}$ are similarly defined. Normally, the sampled wearable gait recognition sensory data are represented in the corresponding sensor coordinate system.

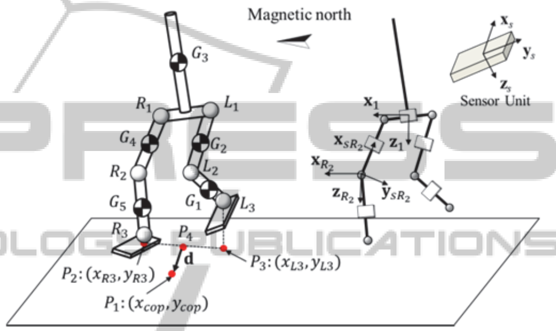

Figure 5: Coordinate definition of gain recognition task.

Due to motion acceleration, the accelerometer output is a synthetic acceleration which consists of gravity acceleration and motion acceleration. Kalman filtering algorithm is used to suppress the adverse impact of motion acceleration, and then to estimate the gravity acceleration and geomagnetic intensity in a sensor coordinate system (Zhu 2004). For any sensor unit, the model of Kalman filter is given by:

$$\begin{cases} \mathbf{s}(n) = \mathbf{A}(n)\mathbf{s}(n-1) + \mathbf{w}(n) \\ \mathbf{z}(n) = \mathbf{s}(n-1) + \mathbf{v}(n) \end{cases} \tag{2}$$

where matrix $\mathbf{A}$ is composed of gyroscope measurements ω_x, ω_y and ω_z.

The state vector satisfies

$$\mathbf{s}(n) = \begin{bmatrix} g_x & g_y & g_z & H_x^g & H_y^g & H_z^g \end{bmatrix}^T \tag{3}$$

where g_x, g_y and g_z are the acceleration components of gravity represented in system $\{sP\}$. H_x^g, H_y^g, H_z^g is the geomagnetic intensity vector represented in system $\{sP\}$.

The observation vector satisfies

$$\mathbf{z}(n) = \begin{bmatrix} a_x & a_y & a_z & h_x & h_y & h_z \end{bmatrix}^T \tag{4}$$

where a_x, a_y, a_z are the outputs of accelerometer and h_x, h_y, h_z are the outputs of magnetometer. $\mathbf{w}(n)$ is a covariance matrix of process noise. $\mathbf{v}(n)$ is a covariance matrix of sensor output noise.

The pitch, roll and yaw angle (θ, φ, ψ) of any sensor unit can be calculated as follows:

$$\theta = \begin{cases} \arctan(g_x / g_z) & g_z > 0 \\ \pi + \arctan(g_x / g_z) & g_x > 0 \; and \; g_z < 0 \\ -\pi + \arctan(g_x / g_z) & g_x < 0 \; and \; g_z < 0 \\ \pi / 2 & g_x > 0 \; and \; g_z = 0 \\ -\pi / 2 & g_x < 0 \; and \; g_z = 0 \end{cases} \quad (5)$$

$$\psi = \begin{cases} \arctan(H^g_y / H^g_x) & H^g_x > 0 \\ \pi + \arctan(H^g_y / H^g_x) & H^g_y > 0 \; and \; H^g_x < 0 \\ -\pi + \arctan(H^g_y / H^g_x) & H^g_y < 0 \; and \; H^g_x < 0 \\ \pi / 2 & H^g_y > 0 \; and \; H^g_x = 0 \\ -\pi / 2 & H^g_y < 0 \; and \; H^g_x = 0 \end{cases} \quad (6)$$

$$\phi = -\arctan(g_y / \sqrt{{g_x}^2 + {g_z}^2}) \quad (7)$$

After estimating these angles of all sensor unit, the coordinate values of all joint points (L_i and R_i with i=1, 2, 3) and segment COG points (G_i with i=1, 2, …, 5) can be easily obtained because the length of each segment is known. Then, the real-time gait is well described by all the point coordinate values.

3.3 Fall Detection Method

We investigated forward, left lateral and right lateral fall in this study. The Centre of Pressure (COP) point, which is equivalent to the well-known Zero Moment Point (ZMP), is a good feature to decide whether a fall occurs (Lee, 2006). It is observed that while human is walking, the COP is nearby the supporting foot. If the distance between the COP and supporting foot suddenly increases, a fall may happen.

In the case of an elderly operating the walking-aid robot, the acceleration of human body is usually small. The COP can then be approximated by

$$x_{cop} = \frac{\sum_i m_i x_i}{\sum_i m_i}, \; y_{cop} = \frac{\sum_i m_i y_i}{\sum_i m_i} \quad (8)$$

where (x_{cop}, y_{cop}) is the coordinate value of approximated COP on the ground. m_i is the mass of the i-th segment of human body and (x_i, y_i, z_i) is the coordinate value of point G_i in system {1}.

To identify whether a fall occurs, a significant feature is assumed based on the relative position between the COP and the midpoint of two feet. This feature is denoted by vector **d** (see Fig. 5), which can be calculated as

$$\mathbf{d} = \left[x_{cop} - \frac{x_{L3} + x_{R3}}{2}, \quad y_{cop} - \frac{y_{L3} + y_{R3}}{2} \right]^T \quad (9)$$

where (x_{L3}, y_{L3}, z_{L3}) and (x_{R3}, y_{R3}, z_{R3}) are the coordinate values of points L_3 and R_3.

Empirically, when the user is falling down the norm of **d** will increase suddenly in a certain direction. We investigate the distribution of $\|\mathbf{d}\|$ during the normal walking state by Dubois possibility theory (Dubois 2003). Similar distribution was regarded as normal distribution and estimated to infer the user's walking state.

Firstly, the probability distribution $\{p(n_j) : j = 1, 2, \ldots h\}$ is calculated by dividing the height of each bin by the total number of sample points of normal walking. h is the number of bins for a histogram. Each bin is represented by the centre of interval denoted by n_j. The possibility distribution $\{\pi(n_j) : j = 1, 2, \ldots h\}$ is deduced from the probability distribution by the bijective transformation of Dubois and Prade defined by

$$\pi(n_k) = \sum_{j=1}^{h} \min[p(n_k), p(n_j)] \quad (10)$$

Note that the smaller $\|\mathbf{d}\|$ is, the more stable the human walks. We propose the membership function $\mu(\cdot)$ for 'normal walking' as follows:

$$\mu(\|\mathbf{d}\|) = \max_{n_k > \|\mathbf{d}\|} \{\pi(n_k)\} \quad (11)$$

Based on the above definitions, a very simple fall detection algorithm can described as: (assuming the human walking behaviour is monitored at discrete times, t denotes the current time)

Algorithm 1: (Fall detection).

IF $\mu(\|\mathbf{d}(t)\|) < c$ AND $\mu(\|\mathbf{d}(t-1)\|) < c$ AND … AND $\mu(\|\mathbf{d}(t-k)\|) < c$,

THEN a fall is detected.

where constant c is a small positive number which indicates a very low possibility of '*normal walking*' state. k is assumed to remove disturbance.

4 EXPERIMENT

In this section, several experiments were performed using wearable sensor group to detect human walking gait and falls, as described previously to verify the validity of fall detection method.

Firstly, the possibility distribution of 'normal walking' was obtained as well as the membership function used in the fall detection algorithm. The subject was requested to walk normally for about two minutes. The trajectory of $\|\mathbf{d}\|$ is shown by Fig. 6. Assuming h=10, the probability distribution $p(n_k)$, possibility distribution $\pi(n_k)$ and membership function $\mu(\|\mathbf{d}\|)$ for 'normal walking' are calculated and depicted in Fig. 7.

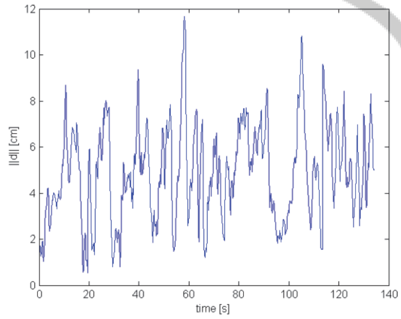

Figure 6: Trajectory of $\|\mathbf{d}\|$ during 'normal walking'.

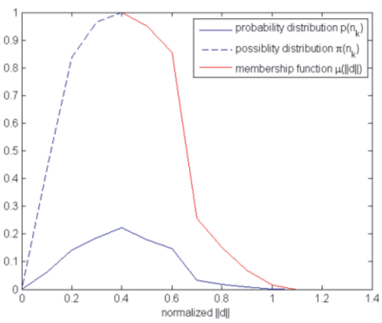

Figure 7: Probability, possibility distributions of $\|\mathbf{d}\|$ and the membership function of 'normal walking'.

After obtaining the membership function, several fall detection experiments were performed. The subject was requested to intentionally fall forward, left and right after walking along with the robot for a while. Constant c is chosen as 0.02. The experiment results of the three cases of falling down are illustrated in Fig. 8, 9 and 10. Applying fall detection algorithm 1, the falls were detected around 10 [sec], 11 [sec] and 15 [sec]. This is coincident to the real experiment and the robot was safely braked to prevent further falling down.

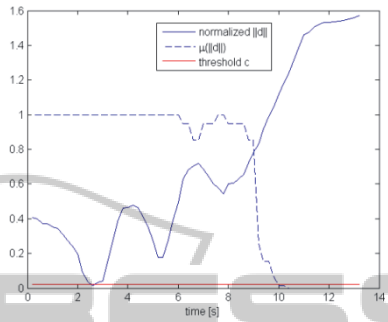

Figure 8: Experiment results of fall forward.

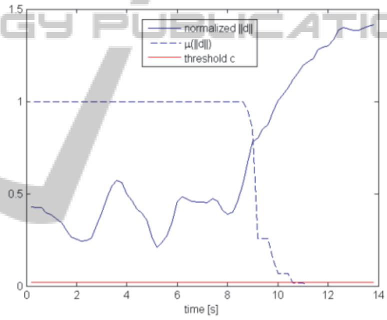

Figure 9: Experiment results of left lateral fall.

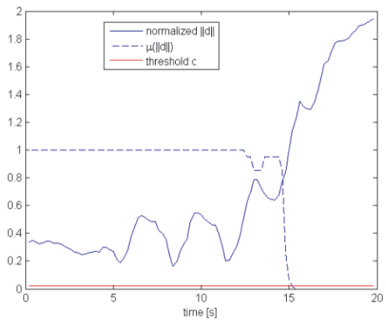

Figure 10: Experiment results of right lateral fall.

5 CONCLUSIONS

In this paper, we proposed a motion control of walking-aid robot based on observing human status by wearable sensors. During normal walking, the robot is controlled by a conventional admittance control strategy. If any fall is detected by wearable sensors the robot will stop immediately to prevent the user from falling down. The proposed fall detection scheme is based on a threshold approach considering the distance between the COP and midpoint of two feet of user. Possibility theory was applied to describe the membership function of ‘normal walking’. The effectiveness of proposed methods is confirmed through experiments.

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