Real-time Fall Detection and Prevention Control Using Intelligent Cane for Human Operator

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Abstract:
This paper proposes a novel human fall detection and prevention method for a walking aid. A three-wheeled omni-directional cane robot was developed previously for aiding the elderly walking. The relative position between the legs of user and the Center of Gravity (COG) of user play an important role in the fall detection when using the cane robot. The COG of user can be estimated from the angle of an inverted pendulum which represents human model. The angle of the inverted pendulum is computed by the support leg position, the hip position, and the force that the human pushes the cane. The fall direction and relative position between the human and the robot play an important role in the fall prevention. The proposed method is verified through experiments.

1. INTRODUCTION

Many countries have entered the aging society very rapidly. Elders suffer from physical and cognitive degradation, such as poor eyesight, lack of muscle strength and so on. In addition, the growing elderly population causes the shortage of people for nursing care. Hence it is significant to design intelligent robots assisting the elders in daily life. Walker-type support systems are important ones among them because the ability of walk is one of the most fundamental functions for humans.

So far, many researchers have developed various intelligent walkers comprising active or passive wheels and supporting frame. Kotani et al. proposed the Hitomi system to help the blind in outdoor environment (1). Fujie et al. developed a power-assisted walker for physical support during walking (2). The Care-O-bot and Nursebot are developed as personal service robots for elderly and disables (3),(4). Yu et al. proposed the Personal Aid for Mobility and Monitoring (PAMM) system to provide mobility assistance and user health status monitoring (5). Hirata et al proposed a new intelligent walker based on passive robotics to assist the elderly, handicapped people and the blind (6),(15).

There are still many deficiencies in the present walker systems. First, many walkers are designed for the indoor environment. Second, most of them are big in size and/or heavy in weight. An indoor robot is often restricted within limited places. Big size makes it impossible to be used in narrow space and heavy weight restricts the maneuverability. Many elders and patients are not so weak that they have to be nursed carefully. Nevertheless, sufficient support, like a cane or stick, is necessary to help them take a walk outside, which enables them to realize high-quality lives or accelerate the rehabilitation. In these cases, an intelligent cane system may be more useful than walkers due to its flexibility and handiness.

In (14),(15) The “GuideCane” and a robotic cane “Roji” are proposed for blind or visually impaired pedestrians to navigate safely and quickly through obstacles and other hazards. In (5),(13), a SmartCane system and Intelligent passive cane are also proposed, which has relative smaller size and nonholonomic constraint in kinematics. The nonholonomic constraint is useful for moving along a path stably, but reduces the maneuverability of the system. In the living environment including the narrow space, the cane system is expected to be movable in omni-directions. Thus, omni-directional mobile platform is needed in the robot design. This kind of platform has been considered in some applications (7),(8). Whereas, their designs are special and not commercially available. Particularly, they are proposed for walker systems but cane systems, which are much smaller in size. Recently, commercial omni-wheels are applied in the area of walker systems. The problem that slender rollers of omni-wheels have limited load capacities is partly solved by the modern technology. In addition, small omni-directional platform can be constructed by this kind of wheels.

In our previous study, an intelligent cane system was designed based on a commercially available three-wheeled omni-directional platform (9). A hierarchical control scheme was proposed with estimation algorithm for human intentional moving direction. Because falling down of the user is the most serious problem for using the walker or cane system, we investigate the fall detection and prevention function of these systems in this study. In (10),(15) Hirata utilized the distance between the user and the robot as a feature to distinguish between the walking state and the emergency state. This distance was measured by a laser range finder (LRF) mounted on the robot. Whereas, this distance is not a significant feature for all possible falling
cases, especially for a lateral falling-down. This will be further analyzed in the following. Vishwakarma proposed a fall model and an adaptive background subtraction method to detect human fall from video clips (11). But background subtraction method is only applicable when there is an immovable background in the processed videos. Some other fall detection methods including wearable sensor based systems, acoustic based systems and video based systems can be found in (12).

2. INTELLIGENT CANE ROBOT SYSTEM

The aim of the intelligent cane is to perform optimized action for the user. These actions include 'guide', 'prevent fall', 'rehabilitation' and so on. Optimized actions depend on the user intention. Therefore, the robot estimates the user's intention from the sensory information. This estimated intention is used to determine the optimized action for the user. Fig. 1 shows the intelligent cane concept.

2.1 MECHANISM OF CANE ROBOT

In this section, we introduce a prototype system of omni-directional type cane robot shown in Fig. 2, which is developed to help the elderly walking. The cane robot consists of an omni-directional mobile base, a metal stick and sensor groups including the force sensor and the LRFs. The omni-directional mobile base comprises three commercially available omni-wheels and actuators, which are specially designed for the walker systems. Despite the small size, the load capacity of this mobile base is up to 50 kilograms. The LRF measures the distances between the stick and the knees, and between the stick and the body, which plays an important role in the function of fall-prevention (9). A six-axis force/torque sensor is used as the main control input interface (Fig. 3). Encoders that are loaded on the omni-wheel vehicle measured the position of the robot.

As shown in Fig. 4, the oriental angle between every to omni-wheels is $120^\circ$. Velocity vector of the vehicle, $(X, Y, \phi_R)$, is calculated by the following equation.

$$
\begin{pmatrix}
\dot{X} \\
\dot{Y} \\
\dot{\phi_R}
\end{pmatrix} = J
\begin{pmatrix}
\omega_1 \\
\omega_2 \\
\omega_3
\end{pmatrix},
$$

where

$$
J = \frac{1}{3}
\begin{pmatrix}
-2 \cos \phi_R (\cos \phi_R + \sqrt{3} \sin \phi_R) & (\cos \phi_R - \sqrt{3} \sin \phi_R) & 1 \\
-2 \sin \phi_R (\sin \phi_R - \sqrt{3} \cos \phi_R) & (\sin \phi_R + \sqrt{3} \cos \phi_R) & 1 \\
1 & 1 & 1
\end{pmatrix}
$$

The vector $(\omega_1, \omega_2, \omega_3)$ means the rotation velocities of omni-wheels. $R$ is the radius of each wheel and $L$ is the effective distance between the center of vehicle and the rim of a wheel.

2.2 CONTROL ARCHITECTURE

There are many possible move modes during the usage of the cane robot. Hirata et al considered three modes including 'normal walking', 'stop' and 'emergency' in their studies (6). Actually, we can divide these rough modes further. For instance, the mode 'normal walking' consists of 'go straight forward', 'turn left', 'turn right' 'emergency' and so on. Normally, different control scheme is required for different move mode. Considering the high-level discrete move modes and low-level motion control scheme based on continuous sensor signals, hybrid system theory is selected as the mathematical tool for the modeling and control design.
A hierarchical control architecture is also proposed, which is depicted by Fig. 5. In the high-level supervising module, current move mode is estimated from sensor signals, which is used to choose appropriate filter to infer the human intention. The inferred human intention is taken as the input of the IBAC controller in the low-level motion controller module, which is proposed in our previous study. All the methods are further illustrated in the following sections.

3. WALKING MODEL OF HUMAN OPERATOR

3.1 DEFINITION OF ORIENTATION FOR WALKING MODEL

The absolute coordinate system \((X, Y, Z)\) is a right hand coordinate system in which the \(Z\) axis means the height, and the original point is set to the initial position of the robot. The support coordinate system \((x, y, z)\) is a relative coordinate system in which the original point is set to the support point. (See Fig. 6)

3.2 SINGLE SUPPORT PHASE MODEL

In the single support phase, the user is modeled by an inverted pendulum, whose dynamics is described by

\[
\ddot{r} - \dot{\theta}^2 r \sin^2 \theta - \dot{\theta}^2 r + g \cos \theta = f/m. \tag{3}
\]

where \(f\) consists of \(f_1\) (reactive force) and \(f_2\) (the force from the robot). \(f_2\) is represented as:

\[
f_2 = -F_x \sin \theta \cos \phi - F_y \sin \theta \sin \phi - F_Z \cos \theta. \tag{4}
\]

where \(F_x, F_y, F_Z\) are forces measured by the force sensor.

The value of \(r\) is almost a constant during the user’s walking. Based on this assumption \(f_1\) is described by:

\[
f_1 = -\frac{m(x\dot{y} - \dot{x}y)^2}{r(x^2 + y^2)} - \frac{mr(x\dot{x} + y\dot{y})^2}{(r^2 - x^2 - y^2)(x^2 + y^2)} + F_x x + F_y y + (F_Z + mg) \sqrt{r^2 - x^2 - y^2} \tag{5}
\]

Therefore, the dynamics of COG is given by

\[
\begin{align*}
mx &= f_1 \frac{x}{r} - F_x, \tag{6} \\
my &= f_1 \frac{y}{r} - F_y. \tag{7}
\end{align*}
\]

3.3 SWITCHING SUPPORT PHASE MODE

The procedure of human walking can be divided into two phases: the single support phase and the double support phase. Considering the double support phase is usually shorter than the single support phase, here we assume that the duration of double support phase is 0. In the double support phase, there are almost no changes of the position and velocity of two legs. Therefore, the switching of different support phases can be detected when the measured velocities of both legs are very small.

4. FALL DETECTION BASED ON DYNAMICAL COG ESTIMATION

4.1 DYNAMICAL COG ESTIMATION

The position of COG is estimated from the positions of legs and body, and the force human exerted on the cane.
Particle filtering technique is assumed as the main estimation tool.

The particle filter is a sequential Monte Carlo algorithm. This algorithm estimate the state of the target by using many particles. This particle has discrete state vector $x$ and the weight $w$ which is related to $x$. The state vector is chosen as: $(x_1, x_2, x_3, x_4)^T = (\dot{x}, \dot{y}, y, \dot{v})^T$ and the dezitlization of (6),(7) is represented as:

$$
\begin{bmatrix}
  x_{1,k+1} \\
  x_{2,k+1} \\
  x_{3,k+1} \\
  x_{4,k+1}
\end{bmatrix} = \begin{bmatrix}
  x_{1,k} - X_{x,k+1} + X_{x,k} + \Delta T x_{2,k} \\
  x_{2,k} + \Delta T (f_{l,k} \frac{\dot{u}}{m} - \frac{\Delta T}{m}) \\
  x_{3,k} - Y_{y,k+1} + Y_{y,k} + \Delta T x_{4,k} \\
  x_{4,k} + \Delta T (f_{l,k} \frac{\dot{u}}{m} - \frac{\Delta T}{m})
\end{bmatrix} + \begin{bmatrix}
  v_{1,k} \\
  v_{2,k} \\
  v_{3,k} \\
  v_{4,k}
\end{bmatrix} \cdot \Delta T .
$$

where $(v_{1,k}, v_{2,k}, v_{3,k}, v_{4,k})$ are the noise of the modeling error. $\Delta T$ means the data update period.

The weight $w$ is determined based on normal distribution.

$$w = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{e^2}{2\sigma^2}\right)$$

where $e$ means the error between the position state vector and the body position $(x_B, y_B)$ and represented as:

$$e = \sqrt{(x_1 - x_B)^2 + (x_3 - y_B)^2}.$$ 

$N(0,\sigma)$.

### 4.2 FALL DETECTION ALGORITHM

The fall situation is categorized into two cases. One is that the fall direction is parallel to the direction from the robot to the user. In this case, a fall can be detected by the distance between the user and the robot. The distance between the user and the robot is defined by $l$. The upper bound of $l$ is denoted by $l_{max}$, which can be measured when user walked normally. A fall is detected at $l > l_{max}$. Another case is that the fall direction is perpendicular to the direction from the robot to the user. The distance along this direction between the center point of both legs and the COG position is defined by $u$. (See Fig. 7)

The safe upper and lower bounds of $u$ and $\dot{u}$, $u_{max}$, $u_{min}$, $\dot{u}_{max}$, $u_{min}$, can be measured when the user walks normally for a long time. Fall is detected when the $u, \dot{u}$ are out of the safe region. To conclude the above discussion, the fall detect algorithm is implemented by the following steps:

1. Measure the distance between the user and the robot.

2. If $l > l_{max}$ then a fall is detected.

3. Estimate COG position using particle filter.

4. Calculate $u(t)$ and $\dot{u}(t)$.

5. If $u(t) > u_{max}$ or $u(t) < u_{min}$ or $\dot{u}(t) > \dot{u}_{max}$ or $\dot{u}(t) < \dot{u}_{min}$ and $u(t-1) > u_{max}$ or $u(t-1) < u_{min}$ or $\dot{u}(t-1) > \dot{u}_{max}$ or $\dot{u}(t-1) < \dot{u}_{min}$ then a fall is detected.

### 5. FALL PREVENTION BY IMPEDANCE CONTROL

#### 5.1 Impedance Control for Intelligent Cane

The low-level motion controller uses a impedance control scheme based on the inferred fall detection. The conventional impedance control uses an impedance model emulate a dynamic system and gives the user a "feeling" as if he is interacting with the system specified by the model.

This model is defined as a transfer function with the user’s forces and toques, $F(s)$, as the input and the reference velocity of cane robot, $V(s)$, as the output. It is expressed as:

$$G(s) = \frac{V(s)}{F(s)} = \frac{s}{Ms^2 + Bs + K}$$

where M,B and K are the mass and damping and parameters respectively.

#### 5.2 Fall Prevention Algorithm

In the fall prevention, it is important to pay attention to the direction along the robot to the user. So we use two control models, one model is impedance control along the direction which head to the user from the robot ($y_B$ axis). The other model is defined for the motion perpendicular to the $x_B$ axis like Fig. 8. This model used admittance control where the mass equals to 0, and $B_d$ is small. Then we have

$$G(s) = \frac{V(s)}{F(s)} = \frac{1}{B_d},$$

and

$$v = F/B_d.$$  

This control method enable the fall direction to be equal to the direction from the robot to the user. It is possible to prevent fall down along $y_B$ axis by control the distance between the user and the robot. So It is desired to keep $l$ to $l_d$. And it is desired that the robot velocity is 0 when $l$ equals to $l_d$. The following impedance model is used along $y_B$ axis.

$$M \ddot{x} + B \dot{x} + K (l_d - l) + f_d = f_y,$$  

where the $f_y$ means the force that the human pushes the robot. And the $f_d$ means the robot’s actuate power. The $f_y$ changes rapidly when the user is falling, so it is desired that $f_y = f_d$ to compensate fall power. Substituting $\ddot{x} = v$ into (14) and applying the digitalization method to (14), we have

$$v_{i+1} = (1 - \frac{B}{M} \delta t)v_i + \frac{K}{M} \delta t(l_d - l).$$
where $\delta t$ means the control cycle time. If $l = l_d$ then we expect $v = 0$. Thus we have

$$v_{t+1} = \frac{K}{M} \delta t (l_d - l).$$

(16)

The above discussion is summarized as the following equations.

$$\begin{cases}
\dot{x}_s = \frac{f_x}{M}, \\
\dot{y}_s = \frac{K}{M} \delta t (l_d - l).
\end{cases}$$

(17)

6. EXPERIMENTS

6.1 EXPERIMENT OF FALL DETECTION BASED ON DYNAMICAL COG ESTIMATION

6.1.1 EXPERIMENTAL CONDITION

- User’s body weight is 45kg and height is 160cm, so $r$ is set to 0.9m.
- The user grasps the handle with his right hand.
- The robot is controlled by the admittance control method.
- The number of the particle is set to 1000, $\Delta T$ equal to 0.1[s].
- $v_1,k, v_2,k, v_3,k$ and $v_4,k$ are set to N(0,0.1).
- $\sigma$ is set to 0.2[m].

6.1.2 EXPERIMENTAL RESULT

The experimental results are shown in Fig. 9 and Fig. 10. A fall is successfully detected when the user bend to left ($t=8.6$[s]). This confirms the effectiveness of our fall detection method.

6.2 EXPERIMENT OF FALL PREVENTION BY IMPEDANCE CONTROL

Experiment is performed when the user lean to the right. The robot is controlled based on the proposed motion control method. The parameters are set as:

$$\begin{cases}
Bd = 5[\text{Ns/m}] \\
\frac{K}{M} \delta t = 3
\end{cases}$$

(18)

Fig. 8 Fall prevent control

Fig. 9 Trajectories of $u$ and $\dot{u}$

Fig. 10 Experimental pictures of fall detection

Fig. 11 The robot and the user position trajectories at fall prevention

Fig. 12 shows the result of the robot and the user trajectory. The origin point means initial position of the robot. It shows that the robot moves to the right direction with turning. Fig. 13 shows that $\theta_f$ rise to $\pi/2$ until $t=0.5$[s]. It means that fall direction is $\pi/2$. $\theta_f$ drop to a lower value until $t=2.0$[s], it means that the fall direction is equal to the direction from the robot to the user. So the proposed method enables the robot to move to the fall direction.

7. CONCLUSION

A new cane robot is designed to help the elderly walk. To prevent the user from falling down, a new fall detection and
prevention scheme is proposed in this study. This scheme is based on the sensor fusion of different sensor resources. Fall model is created by using the simultaneous monitored information of the COG’s positions. The effectiveness is confirmed through experiments.

References


