Ambient Sensor System for Freezing of Gait Detection by Spatial Context Analysis

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Abstract. Freezing of gait (FoG) is one of the most disturbing and least understood symptoms in Parkinson's disease (PD). One of the specificities of FoG is its dependency on the context of the patient, such as current location or a task at hand. Recent advances in assistive technology have strived towards the realization of personal health systems able to prolong independent living capability of people experiencing the symptom. So far, only solutions based on wearable sensing exist, but these systems do not take advantage of the external context for FoG detection. We present the concept and the laboratory prototype of an ambient sensor system designed to enhance its companion FoG wearable monitoring system through precise localization and active mapping of the environment.

1 Introduction

Freezing of Gait (FoG) is a temporary, involuntary inability to initiate or continue movement lasting just a few seconds or, on some occasions, several minutes [1]. FoG is experienced by approximately 50 % of patients with advanced Parkinson's disease (PD). FoG depends on the walking situation. It often occurs on turns, start of walking, upon reaching the destination and in open spaces [2]. It can also occur when people approach narrow spaces, such as doors, and in crowded places [3]. In a home environment, freezing episodes are reported by patients to occur on the same location every day. Other factors that can elicit freezing are set-shifting deficits [4], increased cognitive load such as dual-task, stress, anxiety and depression. Freezing of gait, irrespective of what caused it, is mostly characterized by a decrease in stride length, an increase in stepping frequency preceding the episode and the presence of a highly abnormal frequency of leg movements during the episodes [5].

Some of the patients developed different ways to deal with FoG on their own. This involves various techniques for solving start hesitation like lateral swaying, stepping over someone's foot and stepping over lines on the floor. Observation of

J. Bravo, R. Hervás, and M. Rodríguez (Eds.): IWAAL 2012, LNCS 7657, pp. 232–239, 2012.

these techniques led to the research of cueing. Evidence was found that external "cues" (visual, auditory) may be able to compensate for the defective internal "cueing system" for initiating and maintaining movement, usually facilitated by dopamine [6]. Freezing episode can happen suddenly, particularly when walking, which makes it one of the main causes of falls in PD. Bigger risk of falling causes people to lose their independence [7], aggravates activities of daily living (ADLs) and can have substantial impact on their quality of life.

The research of cueing techniques lead to the development of a few commercial products intended to help patients to improve their gait performance (laser cane, PD Glasses, GaitAid). Disadvantage of current existing products is that they are not adaptable to the walking rhythm of each patient, offering permanent stimulation not useful in most FoG episodes. Recent findings suggest that active monitoring technology [8] has potential to alleviate FoG through timely episode detection and sensory stimulation.

One of the main challenges for adoption of wearable assistants for FoG is to achieve high level of usability, through reliable detection and minimal wearable sensor footprint. We expect that information about patient's external context, like location and orientation during FoG, will be able to improve detection reliability. To obtain this contextual information, we propose the use of ambient visual sensors, hoping that this task could later be implemented as one of the services in vision systems in the homes of the future.

The paper is structured as follows: in section 2, the concept and description of components of the hybrid wearable-ambient system for FoG monitoring are given, in section 3 the laboratory prototype of the ambient system with focus on sensor setup and tested tracking algorithm is presented, while section 4 offers a short conclusion.

2 Ubiquitous Monitoring System for FoG

In our concept for ubiquitous FoG monitoring system, wearable inertial sensor system is used as the main gait monitoring device through the day. Gait monitoring device coupled with a cueing device allows for the treatment of the patient at the point of need at any time. Sensing capacity of the wearable system is expanded with a network of visual sensors installed in the patient's home environment. Use of visual sensors is targeted for non-private areas of a home, such as living room, kitchen and hall. Components of the hybrid system shown in Figure 1 are wearable subsystem running independent FoG detection algorithm, and vision subsystem composed of software modules for image based tracking, environment mapping and context inference that are running on a dedicated server. The remainder of this section gives description of system components and modules.

2.1 REMPARK Wearable System

REMPARK (Personal Health Device for the Remote and Autonomous Management of Parkinson's Disease) is an ongoing three and half year project funded

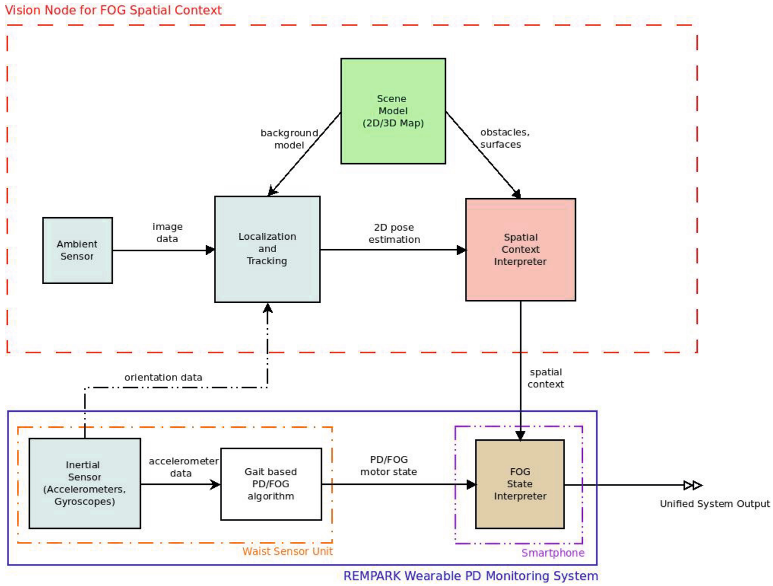

Fig. 1. Ubiquitous Monitoring System for FoG. Wearable system independently detects FoG based on IMU data (blue rectangle), except when in home areas covered with vision sensor system (red rectangle), where users spatial context is also considered.

by the European Commission [9]. The ultimate goal of the project is to develop Personal Health System (PHS) with closed loop detection, response and treatment capabilities for management of PD patients. An important part of the final solution is the possibility to detect and act on FoG episode.

Sensing components of the wearable monitoring system include two inertial sensor units, on a waist and around a wrist. Waist sensor is used for the identification of basic movement related parameters such as posture, stride length and gait speed. The task of the wrist sensor is to detect symptoms of tremor and dyskinesia. Possible actuators are injection pump for drug delivery, the auditory cuing system and Functional Electrical Stimulation (FES) system. FES actuator can be used both as a haptic cueing system, and as a step initiating device in the case of detected FoG episode.

Smartphone is acting as the main control and communication unit of the whole Body Area Network (BAN). Furthermore, smartphone is used as the main input device for collecting patient's input about medication intake and non-motor symptoms. Wearable sensor fixed around the waist is not very valuable for precise indoor localization on its own. However, we expect to be able to utilize this sensor for improved orientation tracking and long term identification in congruence with visual tracking system. Algorithms that run on wearable sensor unit and smartphone are part of the future work and they will not be discussed in this paper.

2.2 Vision System

Vision system has three main tasks: a) identification and tracking of the patient (*Tracking module*), b) automatic analysis of the observed scene (*Scene Model module*), and c) inference about how current location influences the FoG state of the user (*Context Interpretation module*). Output value of the visual system operation is the estimation of probability of FoG based on current location of the patient.

Application driven top-down analysis of requirements of each task determines visual system in terms of the type and spatial distribution of vision sensors.

Tracker Requirements. To infer spatial context in FoG, we are primarily interested in the locomotion behaviour of the patient, addressing the question of how he changes his location over time. Examples from the literature, show that usually two-dimensional (2-D) point representation involving floor map is sufficient for this kind of task [10]. We extracted situations and contextual triggers of FoG that could be identified from two-dimensional motion in a robust and efficient way under realistic conditions. These are turns, start of walking, approach to destination, narrow spaces and locations where FoG occurs every day. For some situations, like turning, 2-D point representation is not sufficient, so we propose 2-D pose (position and orientation) as the minimal representation that should be used in the tracking algorithm.

Scene Analysis Requirements. In their home environment PD patients are likely to encounter narrow passages, such as doorways or dynamically changing spaces created by other people and movable objects. When the space is perceived to be very narrow for the dimensions of their body, adaptive postural changes during locomotion may be necessary to achieve collision-free passage [11]. Experiments with PD patients show that there might be a direct correlation between the width of the narrow space and tendency for FoG episode [12]. If we want our system to be able to use this direct correlations on a dynamically reconfigurable scene, it is necessary to use a floor map with metric values.

Sensor Selection. The need for geometrical relations and real world measurements eliminates the possibility of using monocular color cameras, because they can only do tracking in the image plane, and they are unable to infer distances on the scene. The solution is in the scene recovery by the means of 3-D perception for which there are two possible vision system setups. The first possibility is to use a set of multiple overlapping color cameras per room, which are able to achieve scene reconstruction through joint calibration and solution of the correspondence problem. The second possibility is to use cameras that can sense both color and range data (RGB-D), and which are able to directly recover scene geometry. RGB-D cameras can be installed in non-overlapped mode, focusing only on particular areas in a home. For the laboratory prototype development, we chose to work with the second option.

Context Inference Process. In the case of multiple non-overlapped sensors, context inference process will be done for each RGB-D camera using the concept shown on Figure 1.

Scene Model (SM) module contains 3-D point cloud of the observed scene maintained through periodic updates from the vision sensor. Scene point cloud is updated every few minutes, on occasions when there are no tracked people in the field of view. SM module has dual role in the system. First, updated depth image of the scene is used in the background subtraction process of the vision node tracker. Second, SM module does the planar segmentation and hull extraction of the horizontal and vertical elements, which are obtained from floors, walls and pieces of furniture, and sends them to the Spatial Context Interpreter (SCI) module for further processing.

SCI projects extracted hulls on the floor plane and obtains updated 2-D metric map of the scene (direct geometric representation). Next, SCI analyses the properties of extracted hulls, such as their height, area, relation of vertical and horizontal and tries to infer the meaning of the places on the map, i.e. door or table corner (semantic level representation). Furthermore, SCI employs database, with the history of tracks of the patient and state observations made (historical representation). Combining the set of rules over all three representations, along with the current pose given by the tracker, SCI infers contextual probability of FoG episode. This probability is then published over wireless network and read by FoG State Interpreter (FSI) module running on smartphone device of REMPARK BAN. FSI conducts high level probabilistic fusion of ambient and wearable detector information and produces final system output.

3 Laboratory Prototype

We are currently developing laboratory prototype of the vision system. The prototype development has two main objectives: 1) to prove feasibility of the concept of patient tracking and identification using non-overlapped RGB-D sensors, 2) to establish a way for simple acquisition of video and geometrical data of ADL of PD patients in their home environment.

In our development process, we use one MS Kinect connected with a notebook PC running Linux. The programming is done in C/C++ using *Open Source Computer Vision Library* (OpenCV) and *Point Cloud Library* (PCL) for Kinect data processing, and using *Qt* application framework for user interface design.

3.1 Sensor Properties and Setup

In the laboratory, we use Kinect in the overhead position at a height between 2.2 and 2.4 m and with a downward angle between 20-30 degrees from the horizontal. Although, the nominal operation range of Kinect's range sensor is 0.8 - 3.5 m, we apply it in the extended range of up to 6 m in order to enlarge floor area under observation. Described positioning and the parametric setup of the Kinect sensor, result in the active floor area having trapezoidal shape and size of approximatively 15 m2 (Figure 2.).

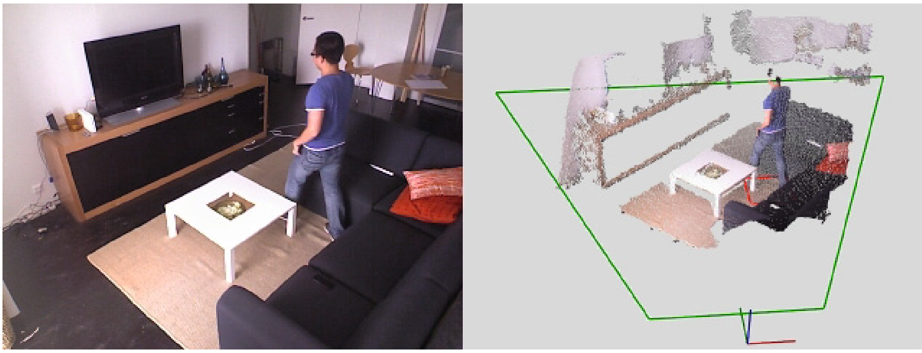

Fig. 2. Left, image of Context Lab at TUE Department of Industrial Design. Right, visualization of the tracking algorithm. Active tracking area has trapezoidal shape (green line). Tracked position of the person is marked by the red rectangle on the floor plane. Coordinate frame shown in the right down corner is *camera base* frame.

3.2 Scene Analysis and Tracking

Plan-view tracking is a computer vision approach which combines geometric analysis, appearance models and probabilistic methods to track people on the 2-D floor plane [13]. The main prerequisite for the successful implementation of any *plan-view* tracking algorithm is to define camera in relation to the floor plane. For our application, we developed a semi-automatic procedure which can detect the floor plane with the minimal input from the user when setting up the system. The procedure is based on planar segmentation by the means of *Random Sample Consensus* (RANSAC) method, and the presumption that the floor plane is among the dominant horizontal planes in the field of view. Two main parameters used during segmentation are the estimate of the camera height in meters, and a minimal number of points for the floor plane.

The procedure takes point cloud of the visible scene as the input, and after applying voxel grid filtering and planar segmentation, it calculates planar equations and hulls of potential candidates for floor plane and visualizes them in the user interface of the application. User can then choose a hull which is the best fit for the floor plane. Usually, only one or two options are offered. After the user input, the axes of the *camera image* frame are vertically projected on the floor plane. Projected axes form an independent vector base for a new reference frame called *camera base* frame. *Camera base* frame is set in exactly under the camera, with X and Y axes spanning the plane of the floor and Z axis pointing up towards camera. This frame is the main frame of reference for tracking in floor plane.

Our adaptation of the the *plan-view* tracking algorithm for the Kinect sensor is based on the work of Munoz [14]. Significant changes were made in the first two stages of the algorithm, foreground segmentation and point projection, to take into account for the specificities of our hardware configuration (different resolution; 640x480 vs. 320x200, different calibration), different software libraries and the role of the tracker towards the rest of the system.

In our version, image-based foreground segmentation has two inputs, the first being depth image of the newest frame from the range sensor and the second being depth image in the background model maintained by Scene Model module. These images are used in the simple subtraction and binary threshold step, to produce unsegmented foreground image. After morphological erosion on the foreground image, contour detection function is applied. Only contours of area size greater than the empirical threshold are kept for further processing. The empirical threshold is set as a size of the upper body half of the grown human that faces camera sideways at the distance of 6m.

Applying foreground mask over color image, and using intrinsic parameters of the range sensor, color point cloud of the foreground is built. This point cloud is transformed into *camera base* frame using the transformation matrix that was calculated during camera setup process. After the transformation, points of the foreground cloud are projected vertically onto the floor plane. From this stage onward, representation maps, people detector and particle filter implementation are done accordingly to [14], so we point the reader to the referenced work for the detailed description. The example of the tracker under operation, as can be seen inside our application, is given at the right of Figure 2.

Preliminary, qualitative tests of the tracker in the laboratory conditions, confirmed that it is able to deal well with the occlusions of the lower extremities produced by the furniture, and that it is able to keep track of the people with sub-meter precision, which are both important properties for our intended purpose. Using non-optimized code with visualization on dual-core P4 2.2 Ghz, we were able to get operation at around 5 Hz.

4 Conclusions and Future Work

In this paper we presented the concept for ubiquitous monitoring system for detection of FoG in PD patients. The concept combines wearable system for gait monitoring with ambient visual sensors for context analysis. In the spatial context analysis, we go beyond localization, as we are also trying to take into account changing characteristics of the surrounding home environment. The focus of the presented practical work is on the implementation of a laboratory prototype of vision system for human tracking. Preliminary results showed that it was possible to adapt chosen tracking algorithm to work with Kinect, and that the algorithm was well suited for handling occlusions in a simulated home environment. The wearable system was presented in terms of sensing components and desired functionality, but none of its algorithms were discussed in this work.

Future work on ambient sensor system will be done in the direction of tracker improvements and scene analysis algorithms. Existing tracker needs to be expanded with the ability of orientation tracking and long-term identification. In scene analysis, we will focus on automatic planar segmentations of 3D scene models and on-line 2-D map building.

Acknowledgement. This work was supported in part by the Erasmus Mundus Joint Doctorate in Interactive and Cognitive Environments, which is funded by the Education, Audiovisual and Culture Executive Agency under the FPA 2010-0012, and in part by the REMPARK project: FP7-ICT-2011-7 287677, Personal Health Device for the Remote and Autonomous Management of Parkinsons Disease.

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