Wandering Behavior Management Systems for Individuals with Dementia

A THESIS
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Dr. Arshia Khan

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It was an honor and a privilege to be a part of the Computer Science department.
Abstract

Alzheimer’s and related dementia are associated with a gradual decline in cognitive abilities of an individual, impairing independent living abilities. Wandering, a purposeless disoriented locomotion tendency or behavior of dementia patients, requires constant caregiver supervision to reduce the risk of physical harm to patients. Integrating technology into care ecology has the potential to alleviate stress and expense. An automatic wandering detection system, when integrated with an intervention module, may provide warnings as well as assistive prompt, in times of abnormal behavior. In this study, we survey existing research on technology aided methodologies and algorithms to detect wandering behavior in movement data of individuals affected with dementia. Our study provides insights into mechanisms of collecting trajectory data and finding patterns that distinguish wandering from normal behavior. Furthermore, we analyze technologies and methodologies used in wandering management, depending on researchers perception of wandering scenarios, and discuss the general challenges of conducting research in this domain. After exploring various existing approaches, we analyze an algorithm that employs vector angles to compute travel direction in spatiotemporal data and verify if including the rate of change of the angles would augment the identification process. In addition, we explore the feasibility of utilizing infrared motion sensor cameras in collecting movement data.
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1 Introduction

Dementia affects the lives of ~47 million people worldwide [69], which is estimated to increase to 131.5 million in 2050. Dementia is a neurodegenerative disease that significantly decreases independence leading to an increase in caregiver cost and burden. According to the Alzheimer’s report from 2016, around 5.5 million Americans suffer from Alzheimer’s dementia resulting in medical expense (professional caregiver and treatment cost) of $259 billion. Family members (unpaid, unprofessional caregivers) spend 18.2 billion hours per year amounting to $230.1 billion [10].

Dementia is sometimes revealed through wandering, which is a pervasive behavioral symptom in dementia patients [41]. It is defined as “a syndrome of dementia-related locomotion behavior having a frequent, repetitive, temporally-disordered, and/or spatially-disoriented nature that is manifested in lapping, random, and/or pacing patterns, some of which are associated with eloping, eloping attempts, or getting lost unless accompanied” [5]. It may be triggered by various factors such as frustration, the intent for socialization or work, boredom or escaping tendencies [41]; however, it is quite unpredictable and therefore requires supervision for detection and arbitration. Unattended aimless roaming of a patient in an indoor environment may lead to agitation, fatigue, vertigo and in extreme cases physical harm due to falling or colliding with objects in the vicinity [10]. Moreover, wandering has been identified as one of the main reasons for nursing home placement or institutionalization [22], as it has proven to be too arduous for caregivers to manage in home environments.

Technological intervention, in detection and mediation of wandering behavior,
would share the load of human labor and, may also improve the privacy and independence of the patient. The detection module can be integrated with an intervention module (i.e. for generating alert signals) to build a real-time system to produce prompt warnings [40]. This would help in reducing immediate health hazards associated with the aimless movement. Additionally, wandering behavior is considered to be correlated with the cognitive state of a dementia patient. Automatically generated records, of wandering frequency and patterns, would aid in keeping track of patients’ cognitive health. As mentioned before, wandering behavior requires a considerable amount of caregiver vigilance and an automated solution has the potential to lower caregiver burden as well as corresponding medical cost.

Several research studies have developed algorithms and GPS based solutions as non-pharmaceutical approaches, to identify and address wandering in the outdoor environment, and demonstrated promising results in terms of data output and human response [87][52][86][40][39][12][20]. Wandering pattern detection in indoor ecology has been examined in studies both in technology domain[33][95][91] and in medical field[42][28][46], underscoring the significance of such an analysis.

A comprehensive survey on technological interventions or ideas, available to assist in wandering management, would contribute to research efforts in computation and cognitive health sector and create a platform for future studies. With that view, we selected several recent literature and investigated what attributes are incorporated in various systems to address wandering management. We draw an overview of the systems, focusing on technologies, underlying strategies or algorithms, scenarios or system goals and searched for overlapping or common grounds, along with challenges inferred from experimental results.

Martino-Saltzman et al. [46] defined four patterns of movement of dementia patients in the indoor settings. One of the patterns corresponds to efficient and pur-
poseful movement; the other three are stated as inefficient and represents wandering behavior. Based on these definitions, Lin et al. [40] formulated an algorithm ($\theta_{WD}$) employed to identify wandering episodes in Global Positioning System (GPS) travel data collected in the outdoor environment. In our study, we analyze this algorithm and investigate the practicability to remodel it for indoor environment, based on data acquired through infra red motion camera sensors.

The subsequent chapters elaborate on the above-mentioned points. In chapter 2, we outline the information necessary to understand dementia and wandering behavior, and user expectation from technology in this sector. Chapters 3 and 4 consists of a survey on proposed or existing solutions for wandering detection or management, built for indoor and outdoor scenarios, addressing various forms of wandering. In chapter 5, we analyze $\theta_{WD}$ algorithm, as well as discuss the usability of infrared motion sensors in this domain. Finally, we conclude in section 6.
2 Background

2.1 Dementia

The Alzheimer’s Association [101][10] identifies dementia as a set of symptoms (rather than a definite disease), triggered by degenerative physical complications such as Alzheimer’s disease or stroke, causing the destruction of neurons or nerve cells at certain regions of the brain. Dementia marks the gradual deterioration of an individual’s cognitive skills such that the person has difficulties performing regular tasks. A non-exhaustive list of cognitive skills affected by dementia includes memory, communication, attention, reasoning and visual perception.

2.1.1 Causalities of Dementia

Alzheimer’s disease is the most prevalent cause of dementia, followed by Vascular dementia, Dementia with Lewy bodies (DLB), Frontotemporal Lobar Degeneration (FTLD), Parkinson’s disease (PD), Creutzfeldt-Jakob disease, Normal pressure hydrocephalus, Huntington’s Disease, and Wernicke-Korsakoff Syndrome [10]. These diseases or physical conditions affect different parts of the brain resulting in a variety of dementia symptoms. Table 2.1 summarizes various causalities of dementia symptoms. An early indicator of the onset of severe cognitive decline may be Mild Cognitive Impairment (MCI), which decreases reasoning abilities noticeably but does not impede independent daily activities.
<table>
<thead>
<tr>
<th>Cause</th>
<th>Symptoms</th>
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<tbody>
<tr>
<td>Alzheimer's disease</td>
<td>• Memory loss</td>
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<tr>
<td></td>
<td>• Mood change</td>
</tr>
<tr>
<td></td>
<td>• Impaired communication</td>
</tr>
<tr>
<td></td>
<td>• Impaired judgment</td>
</tr>
<tr>
<td></td>
<td>• Disorientation</td>
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<tr>
<td></td>
<td>• Behavioral change</td>
</tr>
<tr>
<td></td>
<td>• Impaired walking</td>
</tr>
<tr>
<td>Vascular dementia</td>
<td>• Impaired judgment and reasoning skill</td>
</tr>
<tr>
<td>Dementia with Lewy bodies</td>
<td>• Memory loss</td>
</tr>
<tr>
<td></td>
<td>• Impaired Reasoning skill</td>
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<tr>
<td></td>
<td>• Sleep disturbances</td>
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<td></td>
<td>• Visual hallucinations</td>
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<tr>
<td></td>
<td>• Movement impairment</td>
</tr>
<tr>
<td></td>
<td>• Gait imbalance</td>
</tr>
<tr>
<td>Mixed dementia</td>
<td>• Combination of previous three rows</td>
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<tr>
<td>Fronto-temporal Lobar Degeneration</td>
<td>• Behavioral change</td>
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<tr>
<td></td>
<td>• Impaired language skill</td>
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<td>Parkinson's disease</td>
<td>• Movement impairment</td>
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<td></td>
<td>• Gait imbalance</td>
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<td>• Memory loss</td>
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<td></td>
<td>• Disorientation</td>
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<td>• Behavioral change</td>
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<td></td>
<td>• Impaired walking</td>
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<tr>
<td></td>
<td>• Bladder control loss</td>
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<td>Huntington’s Disease</td>
<td>• Involuntary movements</td>
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<tr>
<td></td>
<td>• Impaired reasoning skill</td>
</tr>
<tr>
<td></td>
<td>• Mood change</td>
</tr>
<tr>
<td>Wernicke-Korsakoff Syndrome</td>
<td>• Memory loss</td>
</tr>
</tbody>
</table>

Table 2.1: Causalities of dementia symptoms [10]
2.1.2 Measure of Cognitive Impairment

**Mini-Mental Status Exam (MMSE)**  In clinical practice, MMSE is used as a short test to determine cognitive capability [27]. Eleven criteria measuring orientation, registration, attention, calculation, recall, language, construction capabilities are utilized to produce a cognitive score ranging from 0 to 30 with a score of lower than 24 representing cognitive impairment.

**Test for Severe Impairment (TSI)**  This test is designed to measure cognition more precisely at a severe spectrum of cognitive impairment. It is a substitution for MMSE, where a person’s cognitive impairment hinders him to participate in the MMSE test. The test is designed to evaluate motor function, general knowledge, perception and communication skill (language skill), short-term and long-term memory, and ability to form ideas, with 21 items divided into six subsections. The total score is 24 with each subsection having a score of 4 [2].

**Global Deterioration Scale for Assessment of Primary Degenerative Dementia (GDS)**  As a measure of the cognitive impairment of a dementia patient, Dr. Barry Reisberg formulated the Global Deterioration Scale(GDS) [71]. This scale is divided into seven stages that categorize the condition of the patient in terms of cognitive decline ranging from *No Cognitive Decline* to *Very Severe Cognitive Decline (Late Dementia)*. Physical (i.e. memory, motor function) and behavioral (i.e. social withdrawal, agitation) attributes, capabilities in Activities of Daily Living (i.e. eat, bath, dress, organize), reasoning skill, and several other functionality levels are used as symptoms to identify each stage [82].
Functional Assessment Staging (FAST) This is another seven stage scaling system, ranging from *Normal adult* to *Severe Alzheimer’s*, based on the level of independence in physical functionality (i.e. walk, sit up, communicate) and capabilities in Activities of Daily Living of PWD [82].

Clinical Dementia Rating (CDR) The most pervasive staging system in dementia related research would be Clinical Dementia Rating (CDR). The patient is evaluated on the basis of memory, orientation, judgment, and problem solving, community affairs, home and hobbies, and personal care and finally assigned one of the five dementia levels ranging from *No dementia* to *Severe* [82].

2.1.3 Behavioral Traits of Person with Dementia

In an attempt to provide care-giving suggestions, [19] lists some common behavioral traits of PWD, which requires caregiver surveillance or intervention to avoid negative circumstances.

Wandering Apparent purposeless travel.

Incontinence Loss of bladder or bowel control.

Agitation Irritability, verbal or physical aggression and other restless behaviors.

Perseveration Repetition of same statement, phrase, or gesture.

Paranoia Distrustful, jealous, or accusatory behavior.

Sleeplessness/Sundowning Lack of sleep and restless behavior at late hours.

Hallucinations and delusions Hear or see non-existing elements.

Shadowing PWD follows around and imitates the actions of another individual, talks or interrupts.
2.1.4 Care Giving for Person with Dementia

Impairments inflicted upon People with Dementia (PWD) renders them vulnerable, even in standard situations of everyday life, especially when cognitive decline is acute. As a result, PWD requires assistance in Activities of Daily Living (ADL), Instrumental Activities of Daily Living (IADLs) (i.e. financial tasks, travel via transportation), maintaining good practice in hygiene, health, and nutrition. People who provide physical and emotional assistance to PWD are referred to as caregivers [10]. Caregivers may be family members or paid professionals such as nursing home staff or personal residential staff. PWD may receive care in the home environment or in a care facility like a nursing home. Several care services are discussed in [10], that accommodates assistance in ADLs and IADLs. Adult day services, Assisted living (housing equipped with facilities to help with everyday activities), Nursing home care, Alzheimer’s special care units (dedicated unit in a nursing home with special services for PWD) all cost substantially and requires a complex set of regulations, equipment and protocols to maintain standard care with safety and avoid harmful situations.

2.1.5 Non-pharmacological Therapies for Person with Dementia

Non-pharmacological therapies are treatments not involving consumption or injection of medication. Technological solutions can aid in developing such therapeutic care systems supporting Activities of Daily Living (ADL) or Independent Living (IL), improving cognitive abilities, and managing mood (depression, apathy, irritability) and behavioral symptoms (wandering, sleep disturbances, agitation, aggression). Different modes of technological interventions have been employed to address several problem domains regarding care of dementia patients. Bharucha et al [15] compiled
some early endeavors to document the possibilities and challenges of devices used to
aid remembrance (Microsoft’s SenseCam[81] or Memory Glasses[24]) and navigation
(Robotic walker[54], Opportunity Knocks[38], Activity Compass), to monitor vital
signs (Medical Mood Ring, Tadiran’s MDkeeper, SmartShirt), agitations[16] or unat-
tended home exits(CareWatch[75]) and also to detect falls (Smart Inactivity Moni-
tor[84], using floor vibration patterns[7] or computer-vision[37][57]). Researchers also
used sensory devices to capture information reflecting the behavior and movement
patterns of patients and to detect and recognize ADL (PROACT [6]). Researchers
have addressed several areas regarding deployment of robots in aiding patients suf-
ferring from dementia. The role of the robot is diverse - including cognitive exercise
with music[88], pictures, voice etc., speech recognition and conversation [76][79], ac-
tivity detection and reaction [80][47], providing a support system for caregivers and
therapeutic treatment[96].

2.2 Wandering Behavior

Wandering refers to the purposeless movement of dementia patients. In chapter
one of [58], Algase et al. present an elaborate discussion on definition of wandering.
They attempted to describe wandering from several perspectives - scientific, clinical
and policy-oriented. A movement behavior can be marked as wandering if patient
traverses a location in a disoriented manner, and this occurs in significant frequency
but not maintaining a specific routine. They also consider rate and repetition of
movement patterns as features of wandering behavior. From a clinical perspective,
wandering is an aimless motion, that may inflict harm on patients and, that has no
harmony with environmental elements. The policy-oriented definition considers the
point of view of a nursing institution. The patients who require more monitoring for
their tendency to stray from employee supervision are marked as wanderers.

The term wandering represents an intricate set of behaviors related to the locomotion of dementia patients. [92] formulated a concise compilation of parameters associated with wandering, based on the particulars presented in [58]. Six characteristics or indicators help frame a well-formed definition of wandering behavior -

1. Repetitiveness
2. Temporal distribution
3. Spatial disorientation
4. Geographic patterns
5. Eloping behavior
6. Negative outcomes

All characteristics may not necessarily be present in one wandering episode. If we inspect the components of each feature in detail, it is evident that each of them requires different methodologies for detection and analysis. Repetitiveness refers to the tendency of following the same routes and visiting same locations without definite purpose. Times and periods of occurrence of wandering can be summarized with a temporal distribution feature. Spatial disorientation is failing to reach a well-known destination, in extreme cases getting lost, also failing to acknowledge obstacles while walking. Geographic pattern addresses four spatial patterns (direct, pacing, lapping and random), also known as Martino-Saltzman movement patterns, observed in wandering trajectories (Figure 2.1). Eloping behavior refers to running away from the authorized area or accompanying personnel. Negative outcomes such as physical exhaustion, accidents may also serve as an indicator of wandering behavior.
2.2.1 Martino-Saltzman movement patterns

Martino-Saltzman [45] deduced four patterns (Figure 2.1) of independent movements of dementia patients in the nursing home indoor environment. Based on the patterns, it can be inferred if an individual is moving without a definite purpose. A direct pattern mostly infers non-wandering behavior where an individual goes directly from one place to another and there is no deviation in the travel path. Random, lapping and pacing patterns could be a sign of wandering. While pacing refers to repetitive linear movement, lapping is repetitive movement in a cyclic manner. The random pattern refers to random movement without following certain criteria and which has no definite goal.

2.2.2 Triggers and Predictors

Wandering episodes may be initiated due to various factors [19]. While some triggers are goal oriented (search for a person, a thing or a place, exercise, complete a task), some are more psychological, emotional or situational (restlessness, agitation, boredom, discomfort). Designing interventions taking into account provocation could help separate a wandering episode from a purposeful movement, reduce false alarms and help resolve an episode faster.

Wandering behavior can be predicted from actions and reactions of individuals at early stages of dementia [100]. These conducts could be treated as scenarios based on which prevention mechanism can be devised. We can categorize these actions as predictors for Spatial Disorientation and Geographic Patterns type wandering episodes in table 2.2.
2.2.3 Non-technological Prevention and Intervention Strategies

Non-technological intervention methodologies suggested or applied by caregivers in wandering management [19] [100] could be beneficial in designing technological solutions to introduce a fraction of automation in detecting and further managing wandering behavior. For example, to prevent elopement or leaving a safe area (i.e. leave bedroom at night) placing door locks away from eye level, putting a cover to hide the door, putting away essential items like the keys, umbrella may work as passive
<table>
<thead>
<tr>
<th>Wandering Type</th>
<th>Predictor Scenario</th>
</tr>
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</table>
| Spatial Disorientation | • Spends more time in regular outdoor tasks  
|                     | • Difficulty navigating in familiar places                                     
|                     | • Attempts to travel to places irrelevant at present i.e. former work place      
|                     | • Attempts to travel to a known place while being in that place               
|                     | • Difficulty finding locations in familiar indoor environment                  |
| Geographic Patterns | • Restless or agitated            
|                     | • Makes repetitive movements                                                   
|                     | • Pacing without purpose                                                      
|                     | • Searches for deceased or unavailable people                                 
|                     | • Unable to complete tasks that requires locomotion                            
|                     | • Nervous or anxious in crowded place                                           |

Table 2.2: Predictors of Wandering Behavior [100]

confinement methods. Exercise at daytime may prevent wandering at late hours. Setting up and maintaining a routine for daily activities, identifying more likely times of wandering, avoiding places that invoke confusion and disorientation, attending to basic needs may immediately decrease wandering episodes and harmful situations but requires constant surveillance. [78] suggests creating an awareness network of family and community, having provisions for quick identification and alerting emergency services as well as knowing destinations and routes frequented by an individual with dementia.
2.2.4 Measuring Wandering Behavior: Algase Wandering Scale

Algase et al. formulated the Algase Wandering Scale (AWS) [3] (and Algase Wandering Scale-Version 2 (AWS-V2) [4]), to measure wandering behavior. It consists of a 10 minutes questionnaire of 28 (AWS) or 38 (AWS-V2) items designed for caregivers. The criteria for measurements include frequency, pattern, quality of movement, boundary transgression, navigation ability, and temporal distribution. The available ordinal responses range from absence to high frequency of criteria.

2.3 User Reaction Towards Technology

It is imperative to design a technological solution (device or software) in accordance with users requirement and comfort, especially for users with special needs. Some research endeavors emphasize conducting pre-study with specific user groups to make the designs more domain and person-centred.

2.3.1 Participatory Design Study

Participatory design, that includes end users in the design process, could be insightful in making technology more practical and usable.

In order to understand the perspective of people with dementia and their caregivers, concerning safe travel outside and technological aid, Robinson et al. [73] conducted participatory design study consisting of three stages - Scoping stage, Participatory design workshops and Prototype development.

Scope Analysis Phase In the scoping stage or scope analysis phase, they held five focus group discussions - two groups of dementia patients, two groups of caregivers and one group of patients and caregivers, with ten dementia patients and eleven
caregivers in total. At this stage they intended to explore how and why technology is needed in safe travel domain. Findings from this stage are summarized in table 2.3.

<table>
<thead>
<tr>
<th>Purpose of Technology</th>
<th>Outcomes of Scope Analysis</th>
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<tbody>
<tr>
<td>• Prevent from getting lost.</td>
<td>• Prevent from getting lost.</td>
</tr>
<tr>
<td>• Aid in usual activities.</td>
<td>• Aid in usual activities.</td>
</tr>
<tr>
<td>• Promote independence and confidence.</td>
<td>• Promote independence and confidence.</td>
</tr>
<tr>
<td>• Reduce caregiver anxiety.</td>
<td>• Reduce caregiver anxiety.</td>
</tr>
<tr>
<td>• Reduce abrupt disruptions in caregiver routine.</td>
<td>• Reduce abrupt disruptions in caregiver routine.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Challenges of Technology</th>
<th>Outcomes of Scope Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Incorporating technology in everyday lives.</td>
<td>• Incorporating technology in everyday lives.</td>
</tr>
<tr>
<td>• Remembered to carry device at all times.</td>
<td>• Remembered to carry device at all times.</td>
</tr>
<tr>
<td>• Device impose constraints on regular activities.</td>
<td>• Device impose constraints on regular activities.</td>
</tr>
<tr>
<td>• Tracking hindrance freedom and privacy.</td>
<td>• Tracking hindrance freedom and privacy.</td>
</tr>
</tbody>
</table>
Outcomes of Scope Analysis

<table>
<thead>
<tr>
<th>Device Design Suggestions</th>
</tr>
</thead>
<tbody>
<tr>
<td>– Two-way communications.</td>
</tr>
<tr>
<td>– Flexibility and adaptability as disease progresses.</td>
</tr>
<tr>
<td>– Guide patients when walking or driving (navigation tool).</td>
</tr>
<tr>
<td>– Integrate easily into daily routine.</td>
</tr>
<tr>
<td>– Portable size and weight.</td>
</tr>
<tr>
<td>– Disguised or less visible to reduce stigmatization.</td>
</tr>
</tbody>
</table>

Table 2.3: User Study Results from Scoping Stage [73]

 Participatory Design Workshop  Specific features and functionality of a potential device are further explored in Participatory design workshop phase employing scenario and artifact analysis methods. These methods involve exploring features user would prefer from a device in best-case, average-case and worst-case scenarios, as well as user reviews on existing technology. Most of the participants from the scoping stage continued their involvement throughout this stage. Findings from this stage are summarized in table 2.4. One imperative conclusion derived from discussions is that it is difficult to develop one single device that incorporates all requirements and user expectations, although there are technologies available to address most requirements.
<table>
<thead>
<tr>
<th>Outcomes of Participatory design workshops</th>
<th>Preferred role of technology</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Aid patients help themselves, without seeking help from other people.</td>
<td></td>
</tr>
<tr>
<td>• Aid in initiating communication with others, when they are lost or unable to help themselves.</td>
<td></td>
</tr>
<tr>
<td>• Aid in generating automatic rescue operation, if they are unable to verbally explain their predicament or destination.</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Artifact Analysis : Mobile phone</th>
<th>• Pervasive and programmable to create desired features.</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Not preferred by patients.</td>
<td>• Forgets to routinely keep phone switched on.</td>
</tr>
<tr>
<td>• Forgets to carry phone.</td>
<td>• Forgets to charge phone.</td>
</tr>
<tr>
<td>• Unreliable in emergencies.</td>
<td>• Unfamiliar device for elderly patients (never used in the past).</td>
</tr>
<tr>
<td>• Complicated user interface (users want simplicity in device).</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Artifact Analysis : iPod Nano</th>
<th>• simple and aesthetic external design.</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Too small, easier to lose.</td>
<td></td>
</tr>
</tbody>
</table>
Outcomes of Participatory design workshops

| Artifact Analysis : General Views | • Device can be customized to individual need.  
• Device should be integrated into user’s daily routine.  
• Device should be disguised as an everyday object.  
• Tracking information should be sent to user chosen person. |

Table 2.4: User Study Results from Participatory design workshops [73]

Prototype Development  Finally, in Prototype development stage, a working device is built, with the help of user (Two people with dementia and one caregiver) feedback on paper prototypes and subsequent refinements. Storyboarding methodology was employed to explore user routines and habits and how the device can be integrated into everyday life seamlessly. To meet the requirements of the two participants (one a driver and the other a runner), researchers implemented two separate devices, one embedded in a notebook and the other in an armband, both having Global Positioning System (GPS) for tracking. Details of the prototype are compiled in table 2.5.

<table>
<thead>
<tr>
<th>Tracking Technology</th>
<th>Prototype Overview</th>
</tr>
</thead>
<tbody>
<tr>
<td>• GPS for outdoor.</td>
<td></td>
</tr>
<tr>
<td>• GMS (Global coMmunication System) chip and web-based service for indoors.</td>
<td></td>
</tr>
</tbody>
</table>
### Prototype Overview

#### Hardware Aspects
- The notebook design measured 13 cm 4.6 cm 10 cm.
- The armband design measured 9.5 cm 7.4 cm 3.5 cm with armband 6.5 cm wide.
- Embedded GPS and GMS modules.
- Chip-set encased in silicone.
- A button to issue emergency signals.
- LEDs for indicating if device is on or issuing an emergency signal.

#### Data Transmission
- Patient device transmits user location to a central web-server continuously.
- Server transmits most recent location of patient device to a caregiver mobile phone or computer, when asked.

#### Panic Button
- Trigger the device to send a message if lost or concerned about safety.
- Message is sent to caregiver mobile phone via the web-server.
- Message is sent as an alert text message.
- The text message contains a link to a map showing patient device location.
User Feedback

- Both versions of the device was too large.
- The armband device kept on slipping due to weight.
- Postcode location is suggested instead of a map based location.
- Address and telephone number printed inside the device aids in disorientation.

Table 2.5: Prototype Developed from User Study [73]

Another research, by Holbo et al. [30], arranged co-design workshops to bring user perspective into design elements. The goal of this study is to explore what people with dementia and caregivers expect from safe walking or travel assistive devices or technologies in general. Three dementia patients, with various levels of cognitive skill, along with their caregivers participated in the study. Comparing the cognitive states and physical capabilities and expressed opinions of the interviewed patients, it is evident that the severity of dementia symptoms increases the desire for technological intervention. Table 2.6 summarizes the results from this study.

<table>
<thead>
<tr>
<th>Suggested Features</th>
<th>Opinions and Design Suggestions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simple Design</td>
<td>• Easy to use and carry.</td>
</tr>
<tr>
<td></td>
<td>• Wrist worn like a watch.</td>
</tr>
<tr>
<td>Suggested Features</td>
<td>Opinions and Design Suggestions</td>
</tr>
<tr>
<td>------------------------------------------</td>
<td>-------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Embedded in mobile phone</td>
<td>• Mobile phone to call or receive calls.</td>
</tr>
<tr>
<td></td>
<td>• Mobile phone with simpler user interface.</td>
</tr>
<tr>
<td></td>
<td>• Caregiver numbers easily accessible in phone i.e. Call home Button.</td>
</tr>
<tr>
<td>Alert Button</td>
<td>• Enables notifying caregiver of emergency situation.</td>
</tr>
<tr>
<td></td>
<td>• Distinguishable I-need-help button</td>
</tr>
<tr>
<td>Remote monitoring</td>
<td>• Enable tracking to ensure safety and reduce caregiver stress.</td>
</tr>
<tr>
<td></td>
<td>• Enable taking break or change route on purpose without added concern.</td>
</tr>
<tr>
<td></td>
<td>• Privacy concern with online tracking.</td>
</tr>
<tr>
<td></td>
<td>• Tracking may be triggered by pressing Alert Button or lack of response to phone call.</td>
</tr>
<tr>
<td></td>
<td>• All time tracking while outside is also suggested.</td>
</tr>
<tr>
<td>Navigation</td>
<td>• Device would assist in finding route to known place if lost.</td>
</tr>
<tr>
<td></td>
<td>• Route Button to ask GPS system for directions.</td>
</tr>
<tr>
<td></td>
<td>• Similar navigation UI as familiar devices in other sectors.</td>
</tr>
</tbody>
</table>
### Suggested Features

<table>
<thead>
<tr>
<th>Fall detection</th>
<th>Opinions and Design Suggestions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>• Automatically detect fall.</td>
</tr>
<tr>
<td></td>
<td>• Notify the local emergency call center with current location</td>
</tr>
</tbody>
</table>

### Health Notifications

<table>
<thead>
<tr>
<th>Health Notifications</th>
<th>Opinions and Design Suggestions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>• Notify user of abnormal physical condition i.e. decreased blood pressure.</td>
</tr>
<tr>
<td></td>
<td>• Reminder of healthy practices i.e. drink water.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Inform caregiver whereabouts</th>
<th>Opinions and Design Suggestions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>• Device notifies user of caregivers location.</td>
</tr>
<tr>
<td></td>
<td>• Decrease the need to call periodically.</td>
</tr>
</tbody>
</table>

Table 2.6: User Study Results from [30]

#### 2.3.2 Study on Specific Technology

A study to collect opinions and ideas of users, concerning GPS device as assistive technology for people with dementia, is conducted by McCabe et al. [50]. Traveling or walking safely and independently might be a challenge for dementia patients due to their propensity for wandering behavior. In focus groups (total 20 participants consisting of dementia patients and caregivers), discussions were held about existing strategies of safe travel, assistive technology for facilitating independence and other qualitative factors and usability of a GPS device. The discussion of themes and topics and conclusions are summarized in table 2.7.
<table>
<thead>
<tr>
<th>Theme</th>
<th>User response</th>
</tr>
</thead>
<tbody>
<tr>
<td>Need for Safe walking Device</td>
<td>• Positive response</td>
</tr>
<tr>
<td></td>
<td>• Will promote independence and self confidence</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Existing strategies of Safe walking</td>
<td>• Guide dogs</td>
</tr>
<tr>
<td></td>
<td>• Assistance from community acquaintances</td>
</tr>
<tr>
<td></td>
<td>• Stay within a familiar area or <em>Safe zone</em></td>
</tr>
<tr>
<td></td>
<td>• Avoid unsafe areas</td>
</tr>
<tr>
<td></td>
<td>• Phone call to taxi or caregivers</td>
</tr>
<tr>
<td></td>
<td>• Stop walking if lost and wait for help</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Purpose of GPS Device</td>
<td>• Increase independence, confidence, quality of life</td>
</tr>
<tr>
<td></td>
<td>• Increase safety and security, reduce risks</td>
</tr>
<tr>
<td></td>
<td>• Reduce stress of patient and caregiver</td>
</tr>
<tr>
<td></td>
<td>• Reduce burden of caregiver</td>
</tr>
<tr>
<td></td>
<td>• Call for help or alert caregivers</td>
</tr>
<tr>
<td></td>
<td>• Guarantee of being found if lost</td>
</tr>
<tr>
<td></td>
<td>• Travel in new or unfamiliar places</td>
</tr>
<tr>
<td>Theme</td>
<td>User response</td>
</tr>
<tr>
<td>------------------------------</td>
<td>-------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Ethical Concerns</td>
<td>• Safety is Prioritized over privacy</td>
</tr>
<tr>
<td></td>
<td>• Embarrassment of using a device</td>
</tr>
<tr>
<td></td>
<td>• Compared to criminal tagging</td>
</tr>
<tr>
<td></td>
<td>• Invasion of privacy</td>
</tr>
<tr>
<td></td>
<td>• Social stigma around dementia and device usage</td>
</tr>
<tr>
<td>Design Suggestions</td>
<td>• used flexibly to meet a range of needs</td>
</tr>
<tr>
<td>Design: Alert issuance</td>
<td>• <strong>Alert Button</strong> on device to send emergency signal or message</td>
</tr>
<tr>
<td></td>
<td>• Easily accessible dedicated button</td>
</tr>
<tr>
<td></td>
<td>• Receivers of alert messages: caregiver, known person, police</td>
</tr>
<tr>
<td></td>
<td>• Alert received by a portable caregiver device available at all times</td>
</tr>
<tr>
<td>Design: Communication medium</td>
<td>• Internet is not preferred for lack of usage skills of PWD.</td>
</tr>
<tr>
<td></td>
<td>• Mobile network based communication (SMS or phone calls) preferred.</td>
</tr>
<tr>
<td></td>
<td>• Two-way method of communication between PWD and caregiver</td>
</tr>
<tr>
<td>Design: Track real time</td>
<td>• Caregiver device with UI similar to other navigation devices to track PWD</td>
</tr>
<tr>
<td>Theme</td>
<td>User response</td>
</tr>
<tr>
<td>------------------------------</td>
<td>-------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Design : Physical attributes</td>
<td>• Inconspicuous, not visible at plain sight</td>
</tr>
<tr>
<td></td>
<td>• Could be worn hidden under clothing</td>
</tr>
<tr>
<td></td>
<td>• Small, unobtrusive</td>
</tr>
<tr>
<td></td>
<td>• Fixed or difficult to remove</td>
</tr>
<tr>
<td></td>
<td>• Need caregiver assistance to attach device</td>
</tr>
<tr>
<td></td>
<td>• Wrist worn device design or other familiar designs (pendant or box)</td>
</tr>
<tr>
<td></td>
<td>• A marker to remind purpose of the device</td>
</tr>
<tr>
<td>Design : Battery</td>
<td>• Clear and correct information about battery life from manufacturer.</td>
</tr>
<tr>
<td></td>
<td>• Long battery life (Device may be forgotten or inaccessible if frequent charging is required)</td>
</tr>
</tbody>
</table>

Table 2.7: User Study Results from [50]

In an attempt to analyze the feasibility of employing a GPS tracking device to locate wandering patients, Wan et al. [99] designed a prototype with the following design principles - reliable, stores movement path history, flexible at system configuration, support multi-person monitoring, has an elderly friendly user interface, navigation functionality and embedded contact list and other information, and distribution of workload between web server and mobile device. The prototype consists of a GPS embedded mobile device with tracker application, a web portal and an iPhone.
application for remote monitoring. It has provisions to set up safe zones, navigation aid and notifications for patient and caregiver, and automatic and manual location data transmission modes.

A qualitative user evaluation was conducted in a dementia care home, a hospital ward and a family residence. At the care home, employers suggested using advanced technology might be challenging for older employees, as they have only limited exposure to such devices and has difficulties using the computer. In the hospital ward, GPS could not accurately locate patients inside the hospital building, which is important in this environment, as patients are not confined to locked rooms and wander off in different locations inside the hospital building. Moreover, as the hospital internet connection was too slow, the researchers provided the staff with an iPad with a better internet connection and the monitoring application. The staff was reluctant in using an expensive device in such an open environment. Also, a patient wandered off undetected, as the system failed to trigger a wandering notification alarm due to battery failure. This suggests the need for a low battery power alarm. Reliability is imperative in a technological solution, especially in emergency situations, as individuals may become dependent and accustomed to a device and its failure might go undetected, leading to precarious circumstances. In contrast, the caregiver of the dementia patient in the family residence considered the tracking device to be helpful in promoting safety and independence as well as reducing stress.
2.4 Technology Explored in Wandering Management Research

In this section, we will summarize a few common technologies that are being employed in studies discussed in later chapters. We would briefly describe the technologies, their connectivity and communication features.

**Radio Frequency Identification (RFID)**  Research studies employ Radio Frequency Identification (RFID) tags to track patients movements within an indoor space. An RFID reader uses an electromagnetic field to detect those tags. One advantage of RFID is that it can be used to track objects with tags and the readers are not required to be in a very close proximity to each other. The range of RFID varies from 10cm to 200m depending on underlying technology and design. There are two types of RFID tags used in literature: Active and Passive. Active RFID tags contain local power sources capable of a larger area coverage but are more expensive and larger. Passive RFID tags are not locally powered and acquire power from radio waves transmitted by a reader using a magnetic induction technology resulting in a shorter radius of coverage. Point of failure of Active RFID would be battery embedded in tags.

**Ultra-wide Band Impulse Radio (UWB-IR)**  UWB-IR is used to track the activities of patients (and their collapse), rather than just location, which requires more precision than infra-red or other course-grained sensors fail to provide. UWB-IR is a radio technology communication with high-bandwidth (500 MHz to several GHz). Depending on the application, it can provide either short-range low-data-rate or long-range high-data-rate service, making it versatile in terms of communication.
Moreover, it is less susceptible to distortion of signal due to multi-path interference and more capable of parallel transmission than narrowband communication. It is claimed to be safer for human subjects with less than -41.3dBm/ MHz electromagnetic energy emission. It is capable of detecting nuances in movements. A UWB-IR generator consists of transmit/receiver antennas that are mounted on walls. The authors from [63] claim this technology to be unobtrusive, which makes it preferable for human subjects.

**Global Positioning System (GPS)**  We notice that most of the proposed solutions for outdoor wandering management utilize Global Positioning System (GPS) to determine patient location. GPS utilizes time and location data transmitted by several satellites to calculate geolocation (longitude, latitude, elevation) of a receiver. Although the accuracy of GPS data may be affected by environmental elements, it is still a reliable, cheaper solution that is embedded in the most mobile communication technologies.

**WiFi**  WiFi, a wireless local area network (WLAN) technology, is built on IEEE 802.11 standards available from 1998. Nowadays, both mobile and desktop devices in indoor environments are compatible with WiFi technology. These devices connect to the Internet using WLAN and a wireless access point (hotspot). In the outdoor environment, various public locations and transportation services are equipped with WiFi access points enabling connectivity of mobile devices, thus increasing the usability of the same system in both indoor and outdoor scenarios.

**Global System for Mobile communication (GSM)**  GSM is a standard for cellular networks used by mobile devices for communicating using phone calls or (SMS). It is specifically built for second-generation mobile networks. General Packet Ra-
dio Services (GPRS) is a data communication method integrated into GSM. Several systems for wandering management utilizes these services.

**Geographic information system (GIS)**  "GIS technologies integrate a range of geographical information into a single analytical model, in which diverse data are georeferenced to cartographic projections"[43]. GIS applications enable storage, manipulation, and visualization of geographic information or maps and give provisions to embed, edit and analyze spatial data in maps.

**Bluetooth**  Bluetooth is a wireless technology used for short range (1001,000 ft physical range) point-to-point data transmission between two coupled devices. It utilizes short-wavelength 2.402–2.480 GHz frequency band radio waves facilitating both short burst data transmission and continuous data streaming [102]. Introducing broadcasting mechanisms, it is expanding its application in Smart building paradigm. It is maintained by Bluetooth Special Interest Group (SIG).
3 Survey: Frameworks for Wandering Management

In this chapter, we discuss existing systems or algorithms that address the issue of wandering in a broader spectrum. The proposed solutions, that we came across in our research, cover both outdoor and indoor scenarios. We are going to list the technologies, proposed or utilized in existing literature as well as real-world devices, in wandering management. As a precursor to formulating a robust algorithm for detecting wandering behavior, a survey on existing systems, would help delineate practical and effective approaches along with limitations, disclosing opportunities for future research.

Most, if not all, systems that we mention here, leverage technologies, frameworks or algorithms from computing and electronics domain, rather than being built exclusively for the medical domain. As a result, technology, used in building a system, change or rather evolve with new inventions in various sectors in information technology industry. This is clearly evident when we compare Opportunity Knocks, which was proposed in 2004, with similar solutions like iWander [87], iRoute [31] and La-Casa [29], which were published in 2010, 2011 and 2012 respectively. To collect data, Opportunity Knocks uses Bluetooth sensor beacon and General Packet Radio Service (GPRS) enabled cell-phone. The sensor beacon sends information to cell-phone, which in turn forwards this information to a remote server, that computes the location of the user using Geographic Information System (GIS) database. Merging
these various platforms robustly and efficiently is challenging, considering connectivity, latency and data loss. In subsequent solutions [31][87][29], researchers moved on to Android smart phones, which have comparatively advanced location sensory and storage mechanisms (GPS, Google map and Cloud database), leveraging applications embedded in the same device.

GPS (Global Positioning System) is a prevalent technology in research endeavours regarding tracking patients in outdoor environment [86] [40] [39] [12] [20] [14]. On the other hand, detecting wandering in an indoor environment needs a different set of equipment, that is suitable for a smaller area of travel - RFID tags, magnetometers as sensory devices and local computer as remote server for data storage and calculation. Some solutions accommodates sending notifications to other end users, to seek for help or informing current status. Some creates interventions for person with dementia to coerce them to a predefined, beneficial action.

### 3.1 Search methodologies

In this study, we aimed to gain insights on current methodologies, the result of technological intervention and related challenges, in the domain of wandering management, which will provide platform for future design opportunities.

We selected twenty three literature from scientific journal and conference publications. Additionally, we reviewed eight commercially available systems to explore technologies employed in real world scenarios.


We excluded literature concerning dementia diagnosis, solutions for dementia symptoms not related to wandering (i.e. memory improvement exercise), activity detection with no specific component for wandering detection, intervention methodologies and other topics not related to technology in wandering management.

3.2 Target scenarios

Design of a system depends substantially on target scenario. This is evident in the variation of scenarios researchers selected, primarily to narrow down to one component or perspective of wandering and deal with the trade off between simplicity and efficiency of a solution.

There are two scenarios in broad spectrum regarding the location of the event (Wandering Behavior): outdoor and indoor. When the patient is confined to a residence or care facility, it comes under the category of indoor wandering behavior. On the other hand, a patient traveling around a much larger area (maybe around a city) falls under the radar of outdoor wandering behavior.

Solutions proposed to tackle outdoor wandering considers travelling in larger areas by foot or by means of vehicular transportation (public and private). For example, Opportunity Knocks [64] (targeted for individuals with mild cognitive impairment) incorporates use-case for public transportation to improve independent life style. [29] describes two scenarios - spatial disorientation (individual can not recognize surroundings and is unable to return to a known place) and goal-oriented disorientation (individual travels to an irrelevant place on purpose due to warped memory). [87] takes into account speed of travel to differentiate between walking and riding motor
vehicle.

*Indoor* wandering monitoring systems deal with scenarios where patient - attempts to leave residential or care facility unattended (elopement), moves around the facility or inside one room aimlessly following some patterns, leaves bed or room at usual sleeping hours or falls down [63], [75].

### 3.3 Target actors

**Primary actors** or users, of the proposed systems, are individuals suffering from various levels of dementia or person with dementia (PWD). Technological interventions may be selected based on patients level of cognitive decline measured by medical scales (Global Deterioration Scale or GDS or Reisberg Scale [72]) (see 2). People with mild cognitive impairment, capable of independent living to some degree, may be equipped with system built to handle *outdoor* wandering. Patients with greater level of cognitive decline, confined to a secured indoor environment for their safety and well being, are most likely to be assisted with systems built for *indoor* wandering management. All throughout our thesis we will refer to person with dementia as PWD.

**Secondary actors** or users of proposed systems are the caregivers (relatives or paid professional helpers) of dementia patients. In most systems, their role is to receive updates of patient status or notifications during critical situations.

Some systems integrates emergency services (Law enforcement or medical services) as actors with approval from caregivers and enable their assistance to ensure PWD safety.
3.4 Outdoor Wandering Management

In this section, we would discuss some systems where outdoor location data plays a central role. Vuong et al. [94] describe a general design, perceived in proposed systems, addressing outdoor scenarios of wandering management. In majority of the systems, the central task is to detect the current location of the patient. A mobile device, (cell phone or other) embedded with sensors collecting location data, is carried by the patient. The location data is sent to a remote server, that runs wandering or anomaly detection applications, and may re-transmit intervention signals to patient. Some systems include a caregiver device in ecology, to monitor patient status and receive notifications.

Standard state-of-the-art location detection, communication and network services are used for tracking and data transmissions. A non-exhaustive list of technologies includes Global Positioning System (GPS), Geographic information system (GIS), Global System for Mobile communication (GSM), WiFi and Bluetooth. Collected tracking data may be stored in databases for learning movement behavior. How long the data should be stored, may depend on the ultimate goal. For example, if the data is collected to infer cognitive health by observing human behavior, then it need to be stored for a longer time, but if the goal is to predict or detect immediate wandering episodes or to estimate current location of the patient, the data can be discarded from memory after a shorter period.

Overview of the proposed system architectures convey a general flow: acquire location data from patient, transmit location data to server, run calculations and transmit result to caregiver, and then transmit back intervention messages to patient (Figure 3.1). One or more components of this flow is present in the discussed systems. The differences lie in underlying technologies and frameworks, influenced by available
3.4.1 General Tracking Systems

A GPS tracking system is proposed by Shimizu et al. in [83] built with a GPS receiver (SONY, IPS-3000) and a mobile device (NTT Docomo, DII-hyper) carried by person with dementia in an unconstrained manner, and a remote personal computer. The GPS receiver retrieves location data from GPS satellites and transmits it to the remote computer via mobile phone over a mobile telephone network. The patients whereabouts can be monitored by a caregiver through the computer. Internet service embedded in a mobile device was not pervasive at that period and authors suggested only mobile network as the medium of data transmission.

Evaluation A feasibility study was conducted by [83], to determine accuracy of GPS device (GPS receiver (SONY, IPS-3000)). Areas with tall buildings decreases the number of satellite channel detection by GPS receiver, resulting in data production once in several minutes. Adverse weather condition i.e. snowfall also reduces data frequency. Environmental elements (weather, terrain conditions, tall buildings, confined areas) has considerable impact on locating wandering person with dementia using a GPS device. The accuracy of the implemented system is one second to several
How the device should be carried by a patient introduces a trade-off between positioning accuracy and user comfort. To test the effect of orientation of GPS device, it was placed in two different orientation and position combinations (horizontal, uncovered, held away from body and vertical, covered, attached close to body), with respect to user, and number of satellite channel detection was measured. Although horizontal orientation yielded more precise data, the authors concluded the more restrictive placement would be feasible in this scenario, which produces results every 2-3 minutes, as opposed to every second. At present, GPS technology can be found embedded in smart phones and how the device is carried has lesser influence on data collection performance.

Calvo et al. developed a system [18], with a view to monitoring elderly people in the outdoor environment. They use a mobile device, running Google Android FLOSS (Free Libre Open Source Software), that has 2G, 3G, Bluetooth and WiFi radios as data transmission mediums. Again, GPS is utilized to retrieve longitude and latitude coordinates. To communicate patients whereabouts to caregivers, they implemented a mobile social network engine (LibreGeoSocial), to build domain specific applications where social graph nodes are mapped to geo-location.

The functionality of this social network application (the study was done in 2009) mirrors social media applications of the present time. Rather than building a new framework, integrating this application to a more prevalent, robust, secure social media platform would be more efficient and relevant in the present context.

Mulvenna et al. in [56], connected a tablet computer in the indoor environment and a mobile phone device for outdoor scenarios, both running a software
(COGKNOW), built to help dementia patients in independent living. The tablet computer works as a hub for sensors, placed at doors and furniture at home. A server is also connected to the system to store patient data, which can be accessed by caregivers through a web interface. Geo-location data is collected using GPS and medium of data transmission is GPRS (General Packet Radio Service). All pieces of equipment used are claimed to be commercially available products, to ensure standard communication and connectivity protocols.

3.4.2 Destination Oriented Travel

IRoute [31] and Opportunity Knocks [64] are two applications, addressing spatial disorientation in the outdoor scenario, using GPS based location data, in aiding destination oriented travel.

Opportunity Knocks The solution proposed by [64], was built with a goal to provide direction to patient, while traveling using public transportation. The patient carries a sensor beacon and a mobile phone. Sensor beacon collects GPS data and transmits to a mobile phone by Bluetooth. Mobile phone, working as a network access point, sends data to a remote server using GPRS network. The server runs a specialized software, that uses sensor data and GIS (Geographic Information Systems) database to track patient location online. Based on location (safe or unsafe route), the server sends back intervention data (i.e. bus route to the safe zone) to the patient phone, that produce audio-visual assistance and alerts. J2ME (Java 2 Micro-Edition) is used as a development platform for the specialized software, that manage all data flow and communication.

Opportunity Knocks [64] was built around a scenario, where person with dementia needs to travel around a city area using public transport. The application, running
on the mobile device, show images of potential destinations (selected from frequently
visited places by person with dementia), based on current location. When user selects
a destination, bus routes are suggested, and instructions regarding the next course
of actions (i.e. bus stop to board or get off) are conveyed. As user progresses along
a route, user locations are processed, to determine if he is on the correct path. If
user diverge from suggested route, warning prompt is produced, and instructions
are updated to bring back user to correct route. The system also has provisions to
differentiate between incorrect travel route and purposeful new route.

**IRoute**  
*IRoute* [31] deploys *Belief-Desire-Intention(BDI)* architecture, to predict
travel in one or more potential travel routes, depending on one or more destinations.
*Beliefs* are a set of facts, *Desire* is the goal to achieve, and *Intentions* are the
set of actions towards that goal. In *IRoute*, previous travel information is leveraged
to predict routes to a goal destination. The system tracks person with dementia in
real time and updates predictions accordingly to location changes. Deviation from
predicted routes, is considered anomalous behavior, and as an intervention technique,
correct route is provided, to coerce person with dementia to follow correct path.
Failure to comply with the guidance, triggers system to notify caregivers.

The *BDI agent* is implemented with *Jadex agent framework*, on an *mobile
phone* with *GPS* capability. GPS location and time data is collected, pre-processed
and passed to *BDI agent*. *BDI agent* is responsible for route prediction, using user
input (list of travel activities, frequency of occurrences, start times and destination
locations) and routes stored from previous travels (a set of time stamps and GPS
location points to a destination location).
3.4.3 Safe-Zone or Geo-fence Centered Systems

Some systems employ algorithms devised around safe-zone paradigm. Person with dementia is considered to be secured if his/her location is inside a predefined zone or virtual geographical fence. In this section, we discuss systems that utilizes this idea.

Safe zones: how to define

This section describes several safe-zone creation mechanism depicted in existing system proposals.

A circular safe zone could be defined with a small radius, initially encompassing only patients residence and adjustable when needed [87]. It is determined by where patients mobile device, on which the system is running, is charged for a extended period of time. Also referred to as geo-fence, it could be defined, centered at home, "with its radius r equal to the distance from a patient’s home to her/his farthest activity location", selected upon interview with person with dementia and caregiver [103]. [13] defines Home zone and Secure zone, where patient lives in Home zone and Secure zone is area outside of Home zone that is marked to be safe. In the system, Home zone can be selected on a map as a point element and Secure zones are created drawing polygons over areas.

Multiple zones could also be defined to indicate safety status of person with dementia. A set of discrete locations (home, close-to-home, far-from-home) could be derived from GPS location data [29]. The zone borders can be defined manually, on a map application, or learned using heuristic, statistical clustering or Bayesian method. A series of safe zones are identified automatically in [59], by mining travel data and detecting most frequented places. Guassian Distribution is utilized to normalize numerous location points, to define a precise safe zone. They also formulate lost zones,
based on locations from where user takes longer to come back home. Zone thresholds are gradually learned from accumulated travel data over time.

Centered at the same point, [35] drew two circles on a map to define zones. The area inside the smaller circle is the safe zone for a person with dementia. The area between the larger circle and outside the smaller circle is considered a warning zone; area outside of the larger circle is considered unsafe. In [53], a set of points are selected as secured places (i.e. home, relative’s house), called Hot Spots. Three circles are defined, centered at each Hot Spot, to mark zones. The zones are defined in a similar way as [35] - familiar area, caution area and completely unfamiliar area.

iWander System developed by Sposaro et al.[87] leverages technology and services embedded in mobile phone device, based on the reasoning that a person carries a mobile phone outdoors all times. They employ Android smart phone with GPS technology to run a JAVA platform application. The application remains passive and collects location data along with weather data from the web-based application. It gets activated when there is a divergence from patients’ regular routes or when the patient travels outside the safe zone. Correct route direction is provided using navigation application with data from Internet. Again, the caregiver is notified via SMS, email or application interface in the form of Google map object. It also takes into account the speed with which the patient is traveling, to determine automobile travel.

iWander [87] is developed on Android platform and runs on Android devices. The system can be divided into two major components - one for detection of wandering behavior and other for intervention.

The detection algorithm applies Bayesian Networks model, which calculates the conditional probability of occurrence of wandering, given - the age of patient, demen-
tia stage of patient, time of day, time outside the safe zone and weather condition. Among the Bayesian network parameters, the age and level of dementia are provided by the user; safe zone, weather and time analytic are collected over time using technologies embedded in the device. It is claimed, that data collected over time improves the prediction performance of the system, and more usage results in improved accuracy. *Support vector machine* followed by a *nonlinear regression* is used to classify regular and abnormal behavior.

The *safe zone* for an individual is determined by frequent charging location of the device. The detection mechanism is initiated if the individual ventures out of the safe zone.

The intervention component of *iWander* is initiated based on the probability from the detection component. A single feedback option is presented to the patient to confirm that they are well, preceded by a notification alert. Lack of response from the user triggers the system to convey direction to the patient using GPS, *Google map* and *Navigation* systems.

If there is no progress, an alert is sent to the caregiver, based on the time spent or weather data gathered from the *Internet*. The system calls several caregivers, using *Google call*, at the same time, and if someone answers the call, it is placed on *speaker mode*, enabling conversation opportunity with the patient. Current location of the patient is also sent to the caregiver via several media. The caregiver can initiate a group call to emergency services, nearest to patient, upon assessing the situation.

For cases where patient is travelling via automobile, the system also incorporates detection mechanisms using *Haversine formula* [74]. Instead of using the Bayesian network based detection component, time of day and travel route data is collected. *Audio prompt* is issued for the patient in case of atypical travel time and route.
Utilizing **Google Voice recognition** and **Google Navigation**, the system conveys direction information leading to destination.

**Discussion** The system accommodates several promising aspects. This can be integrated with Android devices, used regularly, thus eliminating the need to carry additional technology. Most features are automated and do not require a feedback from user, which is convenient in this domain. Learning capability of detection component makes the system customizable for an individual.

One drawback of the system is that the patient must carry the device while travelling outside. If lost or forgotten, system might provide faulty information or gather incorrect training data. It utilizes several application layer services (Google map, Google Voice call, audio prompt, Text messaging and Email applications) to produce alert messages. Therefore, it is required that the applications are available to be invoked when needed.

**OutCare** The system designed by Wan et al. [98] and [97] consists of specialized service oriented interconnected software, running on patients’ device, caregiver device, and data server. Patients’ device is a **mobile phone (Nokia N95)**, equipped with **JAVA** based intelligent agent, **Wi-Fi**, **3G**, and **Bluetooth** for data transmission and communication, and **GPS** service for location tracking. Caregiver device is also a mobile phone, capable of receiving patient status and notifications from the server. The data **server** is equipped with authorized web service, to securely track patient on a map, access patient history data, create **safe zones** and perform related tasks, register patients and caregivers, and update profile information. Alerts are sent via **email** or **SMS** services, in case patient is outside of the safe zone.
Evaluation  User satisfaction (measure of comfort and acceptability) study was conducted in [97], to evaluate the usability of their OutCare system [98], [97]. Given an instruction manual, the participants were asked to perform various tasks associated with different components of the system and finally respond to a questionnaire. They recruited 52 participants, both male and female, aged 17 to 60, from 8 nations introducing diversity. With 92 percent participants successfully completing the assigned tasks, results from questionnaires revealed a score of 5.62 out of 7 in terms of user satisfaction ($t(51) = 3.628, P < 0.001$). 64 percent participants admitted that such solution is needed, and 56 percent showed interest in purchasing the product if available ($t(51) = 6.062, P < 0.001$).

LaCasa  LaCasa [29] employs Partially Observable Marcov Desicion Process (POMDP), to learn known locations of person with dementia, and using that knowledge, detects anomalous travel behavior and provide assistance when needed. The system is comprised of application running on Android platform smart phone and remote desktop machine. Communication between mobile device and server are maintained by TCP/IP protocol XML messages over the Internet. GPS location data is used to locate individual. Safe-zone is created, to ensure safety status, where the patient resides more than 21.5 hrs/day. Wi-Fi connectivity at a known network indicates a safe location. A list of known locations are stored in the server. Data collection is initiated only when the patient is outside of a safe zone, to conserve battery power.

The patient device runs a specialized application, InCense, built for “behavioral data collection that supports an opportunistic and/or participatory sensing paradigm”. When InCense fails to detect a safe-zone WiFi (or cellular) access point, it is triggered, to collect location data using GPS and initiate programmed inter-
vention methods. As intervention methods, stored images of known locations are displayed, audio prompt is played or SMS is sent to person with dementia in case of anomalous behavior.

**Evaluation** A pre-study was designed by [29], to test how the proposed algorithm would perform in learning locations frequented by person with dementia, detecting anomaly in movement data and taking decision to provide assistance. There were 15 participants (5 male and 10 female) in the study, conducted over 20 days, to capture behavioral data, using smart phones, running third party behavioral data collection application (*InCense*). A location is known or frequent, if the participant spends 6 minutes or more, within a diameter of 50 meters. They compared application data with ground-truth data, collected through manual monitoring, resulting in one false negative and on average two false positives (for 16 frequent locations) per participant.

A solution is proposed by Ogawa et al. [61], that utilizes, a low power mobile device (*P-inmaster*, NTT DoCoMo) for person with dementia, an Internet equipped phone (*F503is*, NTT DoCoMo) for caregivers and a remote computer (Pentium 2 GHz Windows, 256 Mbyte memory, 80 GB HDD). The patient device employs *Personal Handy-phone System (PHS)* network. The patient is required to carry the mobile **PHS terminal** at all times.

Every minute, the person with dementia mobile communicates with **receiver antennas** placed every 100m, which in turn transmits **PHS terminal ID** to device installer company in 5 seconds. Location (latitude, longitude) of **PHS terminal** is downloaded through **Internet** from installer company, to the remote PC at the user side, every minute.

The caregiver is notified if location data is outside the threshold of the **safe zone**
(not within 100 meters of home), through the sound system (voice message) of the personal computer (PC), along with an email with static GIF map, depicting persons’ tentative location, downloaded from a map company via the Internet. The caregiver is equipped with an Internet-equipped mobile device to receive voice and email notification.

Evaluation [61] measures localization capacity of their GPS based system by conducting a user study, where a 22 old male participant with normal cognitive abilities wearing a mobile device stood at different locations. The system could locate the individual within 60 meters. They also measured caregiver response time, after receiving an email notification from the wandering person with dementia device, resulting in 10.1-18.5 minutes of rescue time.

Discussion Here, we notice the system needs to act as an intelligent agent, without human intervention. This publication is from 2004; we notice, from later studies, that location map component of the system can be replaced by dynamic Google map. Two different devices and two modes of media are being used, to ensure message delivery to caregiver, which introduces another layer of connectivity. The authors also mention the dimension of the device (51mm x 34mm x 16mm and 27g), which seems feasible to carry around, which is an important aspect in terms of user comfort. There is always a trade-off between usability and performance of devices that are required to maintain online connectivity. The data communication process via a third party, may introduce considerable latency. Also, this procedure requires all-time connectivity, data transmission and power supply of equipment.

Published in 2011, Matsuoka et al. [49] uses the similar communication and sensor receiver deployment mechanism but with a different wearable sensor, formed with
four components, a **mobile phone W-SIM** (50 mm x 30 mm x 5 mm, 10g), a **microphone** (5 mm x 1 mm, 1g), an **amplifier** and a **one-chip micro-controller**, attached to patients clothing.

W-SIM receives patients geo-location (latitude, longitude) through receiver antennas, placed within 100m of the patient, from service provider company, via **Internet**, which is the opposite data flow from that of [61]. A 100 meters antenna scheme is employed in this system like [61]. Data is received every ten minutes from mobile company and stored in the micro-controller, which is then sent to a remote **server computer**, also via **Internet**.

Wandering outside **safe zone** (the location defined in the micro controller) triggers the sensor to record **environmental sound**, using the microphone, and sent to the server computer using **Internet**, along with location data. The server downloads a map of patient location area using **Internet** from a map company, marks location of person with dementia on it and sends these data to the caregiver by **email**.

**Evaluation** [49] leverages environmental sounds to identify location of a wandering patient. In an effort to evaluate their system, the authors recorded sounds from different places and recruited 9 participants with normal cognitive abilities to identify the locations.

They concluded that environmental sounds can be associated with a location. Using sound data along with a map, can be used to locate person with dementia, with 100 percent accuracy. Sound data helps caregivers identify the location and status of person with dementia quicker, when GPS data is not precise enough.

System proposed by Yuce et al. in [103] is dependent on the idea of **safe-zone** and human system interaction. They propose a social network of caregivers (**Caregiver-**
Net), to search for a potential wandering person with dementia. A GPS and GSM SIM equipped wrist-watch tracker, is worn by the person with dementia, which collects location data and sends it to a remote server periodically. Caregivers should also carry a smart phone, with a communication management application running on it. Communication between all devices are maintained using Extensible Messaging and Presence Protocol (XMPP).

An auto intervention mechanism (Call-based Supervision) is employed to check safety status of person with dementia. No-voice communication GSM call is placed through tracker, to inquire person with dementia status. Patient can ensure a safe status by placing a similar call through tracker. Failure to get the safety response call from person with dementia, triggers the system to notify (through XMPP message) all registered caregivers, asking confirmation if patient is reachable. Negative response indicates patient is wandering. Intervention and notification wait times depend on whether person with dementia is inside safe-zone or not.

Wandering state triggers system to increase frequency of location update from patient tracker, to retrieve all GSM numbers of registered caregivers and to send emergency message with patient location. Then it periodically sends the current location of patient to the caregivers, who agrees to volunteer in the search, and eventually stops when a ‘FOUND’ signal (indicating person with dementia is safe) is received from any caregiver.

Photo or images could utilized as a data type in locating a potentially wandering patient (Ko et al. [35]). A GPS and camera equipped smart phone, attached to the body of person with dementia, at a feasible position, takes environmental images periodically and sends to a remote Cloud server, along with GPS location data and time stamp data. Frequency of collecting images can be customized to save battery
power. 2 Gigabytes of Cloud server space is reserved for each person with dementia, with the capacity to store about 820 images. Caregivers can view these information through a Google Map provisioned interface, to trace patients movement path. Even if GPS signal is lost in an indoor environment, the system continues to transmit images of the environment. A safe-zone is defined; stepping outside that safe-zone triggers the system to play a prerecorded intervention audio message to person with dementia, suggesting him/her to return to a known place. Caregivers are notified via phone call. No response from caregivers triggers the system to notify emergency medical services.

*IP Multimedia Subsystem (IMS)* architecture is utilized in the solution proposed by Moreno et al. [53], to model a system suitable for wandering management. They implement IMS Presence Service where Presentities are patients, whose status are make known by the PUBLISH method to caregivers (watchers of Presence Service), through NOTIFY method, who are registered by SUBSCRIBE method. The methods are from SIP/SIMPLE communication protocol.

The location or other information (safe-zone, speed of travel, timestamp) are referred to as presence in this model, and are sent to presence server in XML format, which is Presence Information Data Format (PIDF). IMS server side components (XML Document Management Server (XDMS), XML Configuration Access Protocol (XCAP)) are implemented using OpenIMS and Mobicents. GPS location data is collected using a Android smart phone with IMS Droid client.

**Evaluation** [53] had eleven sub-systems in their system that they evaluated for accuracy, false positive and false negative, running 81 tests, taking up to 21 hours, using three mobile devices. The accuracy of sub-systems were above 75 percent. They
also performed experiment to test connectivity (WiFi, 3G) and device performance (models of mobile devices), resulting in no significant performance difference. They do not clearly specify the participants of the study.

Another system that employs safe-zones is developed by Batista et al. [13]. Their system comprises a smart phone application, that is configurable for patients and caregivers, a server application and a website.

The smart phone application is developed on Android platform and utilizes Google Maps API, and OpenStreetMap tool to define safe zones. The application runs on a GPS equipped smart phone, that collects location data and sends three consecutive locations as XML message format, to server, at definite intervals. Data transmission frequency can be customized according to day, night and emergency period, to save battery life. Moreover, data is only collected if some movement is detected by smart phone accelerometer.

Server side application is developed using Apache-PHP-MySQL tool stack. The website enables caregivers to create and access patient profile, set parameters and monitor alarms, generated by anomalous behaviors (venture outside safe-zone, odd-time, no movement or high-speed movement, system failures).

**Evaluation**  An usability study was coordinated for five months by [13], to verify patient and caregiver reaction to mobile application based technology in wandering management. There were 15 participants with GDS (Global Deterioration Scale or Reisberg Scale, see chapter 2) 2nd, 3rd, 4th and 5th stages of dementia. They conducted a questionnaire based interview for both patients and caregivers. 85 percent of patients were comfortable with mobile and application use, 75 percent felt safer with the application developed by the researchers and 50 percent stated that its not
obtrusive. 62 percent of caregivers felt the patient is safer using the application.

Person-centered paradigm is taken up as design philosophy in [59], with an aim to increase independence and privacy of person with dementia and reduce dependence on caregiver. With ideas based on user study conducted by [30], they designed hardware and software components of a portable GPS device. The device was built using a SIM chip $SIM808$, a micro-controller (Arduino Nano board) and a position and orientation estimator (IMU). GPS location data is collected using a GPS component. Data is transmitted using cellular (GSM and GPRS) technology and SMS and HTTP protocols to a remote server, running SQL database to store the data.

To keep the User Interface simple, only two buttons are visible on the devices LCD display. Pressing $Home$ button displays a visual compass to lead the user home. This feature enables the user to find his own way home and gives person with dementia a chance for independence. The $Alert$ button is there to send the patients current location to caregiver, in case the patient needs assistance. Data visualization and tracking is done by Google Map API.

The authors also formulated an algorithm. For 30 days, the system collects data to learn users “GPS footprint”. Afterwards, in the learning phase, using collected data, the algorithm starts to refine its parameters and to make decisions. A 20 days data window is used to update the parameters further. Distance from home and displacement time are learned statistically as parameters. Exceeding these threshold values would be considered as abnormal elopement behavior. In case of abnormal behavior, the system would generate audio and visual intervention for the user. Also, Martino-Saltzman movement patterns [45] and framework developed by [95] are utilized to identify aimless walking. Safe zone and lost zone mechanisms are also employed to
assist in detecting wandering behavior.

### 3.4.4 Special Features

In addition to a general system design, some special features are proposed to enhance user comfort and reduce false positive warnings.

Distance between caregivers and person with dementia could be measured (there could be multiple caregivers registered with the system), to establish if patient is accompanied by a known person and is indeed safe [53]. Speed of travel can be utilized to automatically detect travel mode (motor vehicle or walking) [53], [87] and define separate intervention and notification protocols for different scenarios.

Even if patient is inside a marked safe zone, he or she might be wandering due to spatial disorientation. A panic button feature may enable person with dementia to trigger an alert situation [53]. In contrast, if person with dementia is travelling outside the safe zone on purpose, an option to enable daily mode or travel mode may also help reduce unnecessary warnings. Wandering at an unsafe hour within a safe zone can be managed by time surveillance [53].

A design decision is, when to send patient location data to caregivers. Data could be sent when there is an abnormal situation or periodically at scheduled intervals. A special feature proposed by [13] enables caregiver to receive last ten locations of person with dementia immediately upon request pressing a panic button.

System failure warnings are effective in avoiding further mishaps, for example - battery alarm (an alarm for indicating a low battery level of device to caregiver) and inactivity alarm (notify caregiver if server does not receive data from patient mobile device at scheduled time) [13] .
<table>
<thead>
<tr>
<th>Citation</th>
<th>year</th>
<th>Data</th>
<th>Sensors</th>
<th>Hardware</th>
<th>Technology/ platforms/frameworks</th>
<th>Data communication protocols/service/network</th>
<th>Algorithm</th>
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<td>XMPP(Extensible Messaging and Presence Protocol)</td>
<td>GSM network (SMS, MMS, A-GPS, GPRS, 3G), Internet, HTTP, XMTP</td>
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Table 3.1: Outdoor Wandering Management
<table>
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<tr>
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<th>Experiment</th>
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<td>Tracking</td>
<td>Notification</td>
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<td>Tracking capacity and rescue time measurement</td>
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<td>Both</td>
<td>No</td>
<td>n/a</td>
<td>No</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>[87]</td>
<td>Movement behavior learning, Anomaly detection</td>
<td>Both</td>
<td>Yes</td>
<td>Proposed clinical trial</td>
<td>No</td>
<td>n/a</td>
<td>n/a</td>
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<tr>
<td>[98], [97]</td>
<td>Tracking</td>
<td>Notification</td>
<td>yes</td>
<td>Clinical trial, 52 participants</td>
<td>Yes</td>
<td>user satisfaction questionnaire, usability test</td>
<td>92% task completion, 75% positive usability</td>
</tr>
<tr>
<td>[49]</td>
<td>Location detection</td>
<td>Notification</td>
<td>Yes</td>
<td>user study, 9 participants</td>
<td>Yes</td>
<td>System test</td>
<td>minimum 15 second sound data for 100% accuracy</td>
</tr>
<tr>
<td>Citation</td>
<td>Algorithm goal</td>
<td>Intervention/Notification</td>
<td>Prototype</td>
<td>Study type</td>
<td>Experiment</td>
<td>Experiment detail</td>
<td>Result</td>
</tr>
<tr>
<td>----------</td>
<td>--------------------------------------------------------------------------------</td>
<td>----------------------------</td>
<td>-----------</td>
<td>---------------------------</td>
<td>------------</td>
<td>--------------------------------------------------------</td>
<td>---------------------------------------------</td>
</tr>
<tr>
<td>[31]</td>
<td>Movement route prediction, Anomaly detection, Assistive</td>
<td>Both</td>
<td>Yes</td>
<td>clinical trial with one participant with MCI</td>
<td>yes</td>
<td>one set of data for single and multiple destination prediction scenarios</td>
<td>system works for one example</td>
</tr>
<tr>
<td>[29]</td>
<td>Movement behavior learning, Anomaly detection, Assistive</td>
<td>Both</td>
<td>Yes</td>
<td>n/a</td>
<td>No</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>[103]</td>
<td>Online location tracking, zone status detection</td>
<td>Both</td>
<td>No</td>
<td>n/a</td>
<td>No</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>[35]</td>
<td>Tracking, fall detection</td>
<td>Both</td>
<td>No</td>
<td>n/a</td>
<td>No</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>[53]</td>
<td>Tracking, Anomaly detection</td>
<td>Notification</td>
<td>Yes</td>
<td>Not mentioned</td>
<td>Yes</td>
<td>Measured performance accuracy of eleven features</td>
<td>Accuracy, false positive and false negative evaluated.</td>
</tr>
<tr>
<td>[13]</td>
<td>Movement behavior learning, Anomaly detection</td>
<td>Notification</td>
<td>Yes</td>
<td>Clinical trial</td>
<td>Yes</td>
<td>usability test, Interview, questionnaire</td>
<td>85% positive usability</td>
</tr>
<tr>
<td>[59]</td>
<td>Movement behavior learning</td>
<td>Both</td>
<td>No</td>
<td>n/a</td>
<td>No</td>
<td>n/a</td>
<td>n/a</td>
</tr>
</tbody>
</table>

Table 3.2: Outdoor Wandering Management
3.5 Algorithms for Spatial Disorientation

Some research focus on formulating detailed algorithms, for detecting spatial disorientation, rather than proposing frameworks.

3.5.1 Anomaly Detection with Zone Boxes

Chang et al. [20] formulates an algorithm to detect anomalous behavior from travel paths or trajectories. Travel trajectory is represented by a series of rectangular boxes, each constituting a sub-trajectory. Top and bottom sides of a box are maximum and minimum latitudes, left and right sides are maximum and minimum longitudes, for that sub-trajectory.

To create and update a box, dimension thresholds are set and incoming location coordinates are used to update the length of the sides of the box. If any one of the sides exceeds threshold, that box is added to trajectory. A new box is created for upcoming location points and the procedure is repeated (figure 3.2).

To establish a trajectory that depicts normal behavior, a history of trajectories are utilized to find overlapping areas. A weight is assigned to each area or region, depending on the number of overlapped boxes, thus creating a weighted trajectory (figure 3.3).

This weighted trajectory is used to evaluate new trajectories, and decide if they represent anomalous or wandering behavior. For a box $B_i$ at time $i$, from a new trajectory, it’s overlapping areas with weighted trajectory is identified. Weighted sum of those areas are calculated, to decide the weight of the box. To calculate the probability, this measure is divided by weighted sum of areas of N, $B_i$ shaped boxes, at time index $i$, from N norm trajectories. A larger value of probability infers a lesser probability of wandering. A person is wandering if probability is lower than 0.2 and
not wandering if probability is higher than 0.8. A value between 0.2 and 0.8, indicates an alert mode.

**Evaluation**  As part of a clinical trial, 8 participants with various cognitive impairment were recruited by [20]. Each participant used public transportation to make 20 trips of .5 to 1.5 hours, from a same source location to participants home. First 10 trips, designed to replicate normal behavior, were used as training set for the system algorithm. Latter 10 trips, devised to have deviations from regular travel routes, were used as test data to evaluate the algorithm. Three individuals followed the participants during the trips, recording travel routes as ground-truth data. Precision, recall and f-measure were used as evaluation criteria, resulting in precision of 90.9
percent) and 95.0 percent recall. Average computation time of algorithm (location data transmission, anomaly detection, alert issuance) was 15.1 to 22.7 seconds.

### 3.5.2 Anomaly Detection with Next Location Prediction

Vuong et al. [94] proposes extension to a next location prediction algorithm (figure 3.4), devised in [66], to incorporate it in wandering management scenarios. The goal is to predict anomalous behavior as soon as possible.

Given a series of locations, the next location (state) is predicted with a confidence
value or level. A prediction counter, associated with that series of locations, keeps count of the correct predictions or prediction confidence. It is increased by one, if predicted result is correct, and decreased by one otherwise. If the counter value exceeds a threshold, the prediction is deliverable or reliable.
Authors from [94] modifies the state predictor, introducing a new update mechanism (Adaptive Confidence Estimation) for confidence counter. This new state predictor tunes confidence counter, based on how frequently a location is visited or an event occurs. They propose to reduce confidence levels in a weighted manner rather than at a flat rate - incorrect prediction associated with more frequent locations are penalized more than less frequented locations.

**Evaluation**  To evaluate their proposed algorithm modification [94] over Confidence Counter predictor, the authors used Augsburg Indoor Location Tracking Benchmarks [65], which includes movement sequences of four participants in an indoor environment. Their algorithm achieved an average accuracy of 88.57 percent and quantity of 76.03 percent, which are better than the scores of other predictor algorithms (Bayesian network, Elman Net, Markov Predictor, Confidence Counter predictor). Here, accuracy is the fraction of deliverable predictions that are correct; quantity is fraction of requested predictions that are deliverable.

### 3.5.3 Wandering Detection with Cycles and Angles in Trajectory

Batista et al. utilized GPS equipped devices in three different studies, to formulate wandering algorithm.

In [86] mobile devices are used to collect location, temporal and acceleration data, that stored in a mySQL server in real time and subsequently in postGIS database, for further analysis with R and Pajek. They hypothesized that randomness is an integral part of wandering behavior. They used the data from their analysis to conclude that, short-length cycles in the trajectory infers to wandering. Based on their theory
and centrality measure described in [26], they proposed a graph representation of trajectory paths and deduced that frequency of nodes in sub-graphs can be used to detect wandering [86].

In a subsequent approach [12], the authors formulated two different algorithms, with a trade-off between accuracy and computational complexity, to identify wandering segments in trajectory data. The first algorithm detects short cycles in the trajectory and the second approach calculates vector angles to detect direction change.

First, they selected a rectangular territory from the previously collected GPS data and divided it into nodes (figure 3.5).

In the first algorithm, they used JGraph from Java library to detect cycles. They used the Schwarcfiter and Lauer’s algorithm [11], implemented in the Java API, to produce a set of cycles from their initial graph (figure 3.6).

The second algorithm utilizes the JAMA (Java Matrix Package) to implement adjacency matrix, that stores the graph information and computes small-length cycles (figure 3.7). To detect the direction and orientation of the individual, the method proposed by [40] (see chapter 4) was used.

**Evaluation** To evaluate their system, they compare trajectories, that contain wandering patterns, with trajectories of patients suffering from mild cognitive impairment, collected during a previous project (SIMPATIC). They selected random subgroups of trajectories from both data set to conduct experiments. Trajectories from SIMPATIC project do not necessarily contain wandering patterns. The authors aimed to see, if their algorithms can detect more short cycles and direction change points in wandering trajectory data than in SIMPATIC data. There is no mention of ground truth data or experiment regarding accuracy and recall scores of algorithm.

For cycle detection algorithm, small cycle of size 2 represents pacing and cycle of
length 3 to 6 can represent lapping. During experiment, it could detect 4 to 7 small cycles of length 2-6 in wandering trajectories. However, SIMPATIC data set did not yield significant number of cycles.
For direction change count approach, the authors hypothesized, that if angle between two consecutive vectors is from 90 to 180 degrees, then there is a change of direction in the trajectory. If there are several consecutive such direction changes in the trajectory, then that trajectory can be marked as wandering.

In the experiment, for wandering trajectory data, more frequent consecutive direction change count is from 2 to 4. However, this does not strongly establish a trajectory as wandering. Pacing and lapping movements should ideally produce more consecutive points of direction change. However, The authors did not comment on
the nature of wandering trajectory data in detail, so it is not apparent how well the
data represents the four geographical patterns.

The authors concluded, that results from the two mentioned approaches should
be combined for a better detection - label a trajectory as wandering, when there are
several short cycles or there are fewer cycles but many direction changes.

They ran another experiment, that plotted frequency of visit at each point in
an area, for both wandering trajectory and SIMPATIC data. Wandering trajectory
data demonstrated no definite path and had some high frequency points, whereas
SIMPATIC data produced some well defined paths with lower frequency points. The
authors argue, that this experiment shows significant difference between the data sets,
although the result published are of two different individuals. As a result, no definite
conclusion can be drawn from this particular experiment.
<table>
<thead>
<tr>
<th>Citation</th>
<th>year</th>
<th>Indoor/outdoor</th>
<th>Data</th>
<th>Sensors/technology</th>
<th>Algorithm</th>
<th>Algorithm goal</th>
<th>Study type</th>
<th>Evaluation criteria</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>[20]</td>
<td>2010</td>
<td>Outdoor</td>
<td>Sequence of locations (latitude, longitude), time</td>
<td>GPS, Personal digital assistant (PDA)</td>
<td>Real time deviation detection with Box trajectory</td>
<td>Anomaly detection, Movement behavior learning</td>
<td>clinical trial (8 participants)</td>
<td>Precision, recall</td>
<td>Precision .90, recall .95, computation time 15.1s to 22.7s</td>
</tr>
<tr>
<td>[94]</td>
<td>2011</td>
<td>Indoor</td>
<td>Sequence of locations (latitude, longitude)</td>
<td>–</td>
<td>State predictors with confidence counter (CC), Adaptive Confidence Estimation</td>
<td>Movement behavior learning, next location prediction, Anomaly detection</td>
<td>Augsburg Indoor Location Tracking Benchmarks</td>
<td>Accuracy, quantity</td>
<td>Accuracy .88, quantity .76</td>
</tr>
<tr>
<td>[12]</td>
<td>2015</td>
<td>Both</td>
<td>Sequence of locations (latitude, longitude)</td>
<td>GPS, PostGIS database</td>
<td>Cycle and direction analysis in travel trajectory</td>
<td>Wandering detection</td>
<td>User Study (wandering data set), SIMPATIC clinical trial data set</td>
<td>Detect cycles, direction change in two data sets</td>
<td>Wandering data set has more cycles, direction change</td>
</tr>
</tbody>
</table>

Table 3.3: Algorithms for Spatial Disorientation
3.6 Indoor Wandering Management

Various works have been done on wandering management in indoor environments, especially in residential and nursing homes.

3.6.1 Smart Home

In an earlier research, Doughty et al. [25] proposed connecting various sensors and actuator devices, distributed across the residence, in accordance with Internet of Things principles. Mat-shaped step sensors, piezoelectric sensors, inductive coupling sensors, passive infrared sensors, door sensors, thermostats are used to sense a broader range of events and activities. Personal handy-phone system (PHS), automatic light sources, alpha-numeric message display, wrist-worn display, and television serve as actuators. Software running on a local personal computer act as the central management device. Also, intermediate devices, to track sensor activation or value-thresholds and to send alarms to actuators, are proposed as wrist-worn devices. Triggered by a door sensor, they send radio beacon to remote authorities.

As data or information transmission mechanism, low power FM radio pulse signal is used, that send ID code of devices. High gain directional antennas are used to locate the source of transmission. For these scenarios, data is transmitted only when an event triggers a sensor. It is imperative that transmission mechanism and actuators perform during those episodes. But sensors should remain functional at all times.
3.6.2 Smart Hospital

A Smart Hospital system architecture is proposed by [60]. In a hospital topology, active and passive RFID tags can be attached to objects and individuals, with RFID readers placed in each doorway. Signals from local readers are aggregated by ward and floor level reader nodes (hierarchically organized) and sent to the central IT server. To enhance the accuracy of the location data, they propose multi-modality, with signals from mobile Bluetooth and Wireless Local Area Network (WLAN) devices.

They emphasize on inter-modal and intra-modal communication improvement, where inter-modal means connectivity among different kinds of sensors, and devices and intra-modal refers to connectivity among a number of sensors of the same type. At the middleware level, the authors suggest using an Application Level Event (ALE) engine, for real-time processing of location data, connecting the sensor layer and the application layer. It triggers events based on the readers’ data and pass the assembled data to the application layer, and similarly convey messages generated at the application layer back to the readers. Here, data sent by readers are of the form $<\text{tag ID, time-stamp, reader ID}>$.

3.6.3 Late Hour Wandering

Night time wandering, due to abnormal sleep pattern, could be hazardous for people with dementia. Supervision to such behavior requires modification to caregiver sleep routine, which consequently disrupts their daily life.

Masuda et al. [48] integrated a system composed of a step sensor, a wandering alarm and a floor illumination component, with an aim to detect if patient is leaving
bed. The step sensor, shaped as a mat to fit into an indoor environment and kept by the bed, if stepped on, gets activated and sends out signal to the wandering alarm component. This component has a **personal handy-phone system (PHS)** terminal, that sends warning notification, with step sensor ID, to caregiver PHS receiver. The step sensor activation also triggers a illumination system, that turns on around the bed area. This intervention is designed to avoid immediate danger (i.e. bump into obstacle) due to wandering in darkness. The system was tested in a hospital, with three participants (dementia patients with wandering tendencies), over a period of four weeks, and was able to detect wandering and produce alarm thirty times.

Another solution is proposed by Rowe et al. [75] to aid caregivers in night-time wandering. It is built to alert caregivers, only when patient leaves bed at night time, thus reduces the need for constant vigilance at late hours. They formulated a list of features the device should have - bed occupancy sensor, caregiver notification (sound-alert, text or audio), locate patient in real time, alarm for going outside, alerts for indoor movements and simple user interface.

The final system consists of various sensors (**bed occupancy sensor, motion sensor, door opening sensor**), wireless receiver and control panel running a software with specialized features. While the components were integrated from commercial products (i.e. commercial home security system’s transmitter-receiver system), the researchers developed the bed occupancy sensor themselves. It is an air bag connected to a transmitter, through an air pressure switch. When air pressure switch changes state (open when air pressure is low or close when pressure is high), the transmitter sends signal (off or on) to a remote receiver.
Evaluation To evaluate their bed occupancy sensor based night time wandering detector, [75] ran a reliability test for two weeks. In their system, unattended home exit is detected by door sensors. Their aim was to lower false negatives (i.e. undetected exit) and false positives (i.e. issuance of false alarms). All sensor data were streamed and stored, later analyzed for system and sensor functionality. For clinical trial, among 55 dementia patient residents, they randomly installed their system in 27 homes and kept 28 homes in the control group. Three patterns of system installations were employed based on patient habits and requirements - issuance of alarm when PWD leaves bedroom, issuance of alarm when PWD gets off and walk away from bed, and issuance of alarm when PWD attempts to leave bed.

A different approach in detecting dementia patient’s late hour wandering or sleep pattern, could be found in a system by Ota et al. [63]. The authors employ ultra-wideband impulse-radio (UWB-IR) to detect specific states of a patient, such as - static on bed, moving on bed, fall down, wander inside room, get in or out of the room.

They pointed out several advantages of UWB-IR. It is a non-obtrusive technology, capable of detecting nuances in movement from afar, preserving privacy and health. Distance of various objects from the sensors, generates a range of received power delays. Also, movements (introducing new object on or near static objects) change the values of power delays, making them detectable. The overall sensor system consist of a UWB-IR generator, a low-noise amplifier (LNA) and a digitizer. The transmit/receive antenna was placed 0.2m above the entrance door.
3.6.4 Prediction Framework

Taking inspiration from the wandering activities listed in Algase Wandering Scale (AWS) [3], a framework for predicting wandering behavior in indoor environment is proposed by Toutountzi et al. [89]. They propose to employ an assortment of sensors (wrist worn step counter, heart rate sensor, switch sensor, 3d-depth camera Kinect) to collect and compile data to detect some of the factors stated in AWS.

For example, increased walking, specially at night time, is an indicator for Persistent walking factor. A wrist worn sensor, capable of counting steps, could be used to collect data, that represents frequency of walking. Increase in such behavior can be a predictor of increased wandering behavior.

Decreased sleep time may lead to wandering behavior. A heart rate sensor can be employed to determine if person is asleep, and subsequently measure average sleep time over a longer period.

Failure to locate a familiar place (i.e bathroom), walking around aimlessly, are signs of spatial disorientation. A switch sensor, installed at the door of a bathroom, may collect data regarding frequency of visit.

Shadowing, repetitive walking, as well as failure to avoid obstacles in walking path, are also factors of wandering. A Kinect 3d-depth camera may be employed to detect these behaviors and accumulate time and occurrences data of such behavior. Gradual increment of such incidents may be predictor of wandering.

Active RFID (Radio Frequency Identification) generated data is used in a series of studies [28] [34], that aims to verify the role of tortuosity in movement data, in predicting dementia. [34] employs wrist-worn RFID transponders along with wall-mounted sensors with UWB (Ultra-wide Band) sensor technology. A real-time location analysis software that is built for the sensors, is run on a notebook computer, which works
as the data processing hub. Data transmission and connectivity are maintained using Ethernet switches and network cables [28].

**Prediction algorithm**  To predict wandering in the Smart hospital mentioned previously, [60] propose a event-based sequence matching prediction algorithm. The goal is to predict the next in a sequence of events. Transitions from one event to another are accumulated from previous data, with a score associated with each pair. With each new event in the sequence, score associated with the transition from previous to the current event is increased by a constant factor. Scores for all other transitions to the current event are decreased by a constant factor. When predicting an upcoming event, the highest scored transition from current event, is selected.
<table>
<thead>
<tr>
<th>Year</th>
<th>Data</th>
<th>Sensors</th>
<th>Hardware</th>
<th>Technology/platforms/frameworks</th>
</tr>
</thead>
<tbody>
<tr>
<td>1998</td>
<td>Activity and event detection (i.e. mobility)</td>
<td>Multiple type</td>
<td>Passive infrared, inductive sensor, identification badge, Piezo sensor, Thermometer, microphone</td>
<td>Desktop computer</td>
</tr>
<tr>
<td>2002</td>
<td>Detect nighttime wandering</td>
<td>tag ID, timestamp, reader ID</td>
<td>Step sensor</td>
<td>Sensor signal receiver, Lighting</td>
</tr>
<tr>
<td>2003</td>
<td>Locate Wandering person in a large facility</td>
<td>sensor activation signal</td>
<td>RFID</td>
<td>RFID tag and receiver, Mobile device, Central server</td>
</tr>
<tr>
<td>2007</td>
<td>Detect nighttime wandering</td>
<td>sensor activation signal</td>
<td>bed occupancy sensor, motion sensor, door opening sensor</td>
<td>wireless receiver, control panel</td>
</tr>
</tbody>
</table>

References:
- [25]
- [48]
- [60]
- [75]
<table>
<thead>
<tr>
<th>Year</th>
<th>Goal</th>
<th>Data</th>
<th>Sensors</th>
<th>Hardware</th>
<th>Technology/Platforms/Frameworks</th>
</tr>
</thead>
<tbody>
<tr>
<td>2011</td>
<td>Detect night time wandering</td>
<td>n/a</td>
<td>ultra-wideband impulse-radio(UWB-IR)</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>2011</td>
<td>Verify effect of tortuosity in dementia prediction</td>
<td>X, Y, Z coordinates wrt fixed origin, transponder number, date, time</td>
<td>Active Ultra Wideband RFID</td>
<td>RFID tag transponder and sensor, Ethernet switch, Network cable, Notebook computer</td>
<td>Ubisense 2.0 software</td>
</tr>
<tr>
<td>2015</td>
<td>Predict existence of wandering behavior</td>
<td>Activity frequency, step count, time of activity, heart rate, location visit frequency, event frequency and time</td>
<td>Wrist worn activity sensor (step counter), heart rate sensor, switch sensor, 3d-depth camera</td>
<td>Kinect</td>
<td>n/a</td>
</tr>
</tbody>
</table>

Table 3.4: Indoor Wandering Management
<table>
<thead>
<tr>
<th>Citation</th>
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<th>Implementation</th>
<th>Evaluation/ Experiment detail</th>
<th>Result</th>
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<tr>
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<td>No</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>[48]</td>
<td>Yes</td>
<td>Yes</td>
<td>System testing, 3 participants, 4 weeks</td>
<td>n/a</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Detected wandering 30 times</td>
<td></td>
</tr>
<tr>
<td>[60]</td>
<td>No</td>
<td>No</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>[75]</td>
<td>Yes</td>
<td>Yes</td>
<td>Control group experiment, 55 residence</td>
<td>Not reported</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>Detection rate 95%</td>
<td></td>
</tr>
<tr>
<td>[34]</td>
<td>Yes</td>
<td>Yes</td>
<td>System testing, Detect scenario</td>
<td>-</td>
</tr>
<tr>
<td>[89]</td>
<td>No</td>
<td>No</td>
<td>n/a</td>
<td>n/a</td>
</tr>
</tbody>
</table>

Table 3.5: Indoor Wandering Management
3.7 Commercial Devices

Wandering behavior, requiring an extensive amount of supervision, inspires an assortment of assistive commercial products [1] that leverages current technologies. Here, we summarize (in table 3.6) selected products, in an effort to provide a brief idea about how products can be utilized to share the burden of care giving.

**Trax** [90] It is a wearable online GPS tracker that accumulates and transmits location, speed and orientation data through cellular network to smart phone application. With dimensions 2.2” x 1.5” x 0.4” (55 x 38 x 10 mm), the device has battery life up to 3 days and . The application enables setting up unlimited safe perimeters or Geofences. When individual with dementia steps out of that zone at predetermined times, a warning notification is issued to caregivers.

**Safe Link** [77] This is another wearable real-time GPS tracker, that periodically sends location data (geographic coordinates) to a cloud based remote server over the internet, which caregivers can access via internet through a website. It is required to be charged and worn at all times, to provide substantial service. The device is equipped with an alert button to seek for help in case of emergency. It can be carried around in various ways (i.e. belts, key chains, bags, shoes).

**Project Lifesaver** [67] As part of a search and rescue program, this device is a location transmitter, worn around the ankle, that tracks if the person is wandering. If wandering behavior occurs, caregivers notifies an associated agency with trained team with recovery time of thirty minutes. PLI-1000 PERSONAL LOCATOR SYSTEM is a device under Project Lifesaver program specially built for caregiver use without professional involvement. It is a radio frequency based tracking system consisting
of a personal receiver, with Yagi antenna (caregiver device) and a 216 MHz 60 day transmitter (worn by PWD).

**PocketFinder** [68] Being a universal tracker, this device is equipped with GPS/A-GPS, Cell ID, and Google Wi-Fi Touch Triangulation as locator technology, with Google Premier Mapping as a medium to display location of carrier. It is carried by the PWD and its whereabouts can be tracked using a mobile application. Location information is updated every 60 seconds. It has a battery life of up to one week. It supports creation of unlimited number of safe zones and enter and exit notification to caregivers. Speed alert and low battery alert features add to safety of PWD. 60 days trajectory data is stored for viewing. This is a potential feature to introduce an intelligent system in the ecology, to learn travel behavior from data and issue automatic alerts in case of anomalous behavior. The dimensions of the device are 1.6” x 3” x 0.6”, weighing 1.7 oz.

**Mindme Locate** [51] Designed as a pendant, Mindme locator device is used to track its carrier on line using a website. GPS is accurate up to 10 meters, transmitting data every 4 minutes, which can be accessed through a dedicated website. It is equipped with multi-network SIM card, widening its connectivity range with multiple cell networks. A safe zone radius can be outlined by the caregiver. If the person travel outside the zone, an alert notification is sent to the caregiver. The device can be carried in various ways conforming to user comfort. Dimensions of the GPS device are 60mm x 44mm x 14mm, weighing 40 grams, with battery life of 48 hours and a low battery alert system.

**GPS Smart Sole** [85] Here, GPS technology is embedded in a shoe sole to be put inside a shoe. GPS data (Latitude/Longitude, Speed, Bearing, Altitude) is collected
in real time, compiled into a trajectory history report, to be accessed by caregivers via smart phone application or desktop computer browser. Cellular network is used to transmit GPS data to remote server. Geofence can be set up for receiving email or SMS alerts in case of travel in unwanted territory. Battery life ranges from 18 to 48 hours.

**iTraq** [32] Connected to an smart phone application, this is a universal tracking device with GPS, temperature sensor and accelerometer (to detect motion or fall). It utilizes GPS, Cellular, Wi-Fi, iBeacon microlocation technology to collect more accurate location data. Data can be accessed via internet through dedicated smart phone application. This also has a **SOS button** for PWD to seek help at emergency situations, that sends current location of PWD to caregiver. The newest version of the device has longer battery life (two months), wireless charging ability, and is water, dust resistant, all of which are beneficial features for individual with dementia. It is also equipped with Geofence feature. Dimensions of the GPS device are 2.05” x 2.05” x 0.43”, weighing 1.41 ounces.

**AngelSense** [8] This device keeps track and learn travel patterns of individuals with dementia, even in indoor environments. It generates an alert to caregivers in case of any unfamiliar activity (increased speed, delays or unfamiliar place). Data transmitted are locations, routes and transit speed along with environmental sounds, to aid in locating a wandering person. It is provisioned with communication mechanism between caregiver and PWD, as well as emergency help seeking button for PWD. Dedicated application running on caregiver mobile device enables tracking and managing preferences. The device can be attached to patients clothing, only to be detached by caregiver.
<table>
<thead>
<tr>
<th>Product name</th>
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<th>Sensor</th>
<th>Features</th>
<th>Data</th>
<th>Data Transmission</th>
<th>Software</th>
<th>System Components</th>
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<td>GPS, Microphone</td>
<td>SOS button, Phone Call, High-speed alert, Unknown place alert</td>
<td>locations, routes, speed, sounds</td>
<td>Internet, Cellular network</td>
<td>Mobile App.</td>
<td>GPS device, Mobile phone</td>
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<tr>
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<td>Versatile</td>
<td>GPS</td>
<td>GeoFence</td>
<td>Location, Temperature</td>
<td>Internet, Cellular network</td>
<td>Mobile App.</td>
<td>GPS device, Mobile phone</td>
</tr>
<tr>
<td>GPS Smart Sole</td>
<td>Shoe</td>
<td>GPS</td>
<td>geofence, No-Motion Sleep Mode</td>
<td>Location, Speed, Bearing, Altitude</td>
<td>Internet, Cellular network</td>
<td>Mobile app., Website</td>
<td>GPS shoe sole, smart phone, desktop</td>
</tr>
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<td>Versatile</td>
<td>GPS</td>
<td>geoFence, multi-network SIM card Low battery alert</td>
<td>Location</td>
<td>Internet, Cellular network</td>
<td>Website</td>
<td>GPS device, desktop computer, Mobile phone</td>
</tr>
<tr>
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<td>Versatile</td>
<td>GPS, Cell ID, Google Wi-Fi Touch</td>
<td>SOS button, Geofence, Speed alert, Low battery alert</td>
<td>Location</td>
<td>internet</td>
<td>mobile app</td>
<td>GPS device, Mobile phone</td>
</tr>
<tr>
<td>Project Lifesaver</td>
<td>Ankle</td>
<td>radio signal</td>
<td>–</td>
<td>–</td>
<td>radio frequency</td>
<td>–</td>
<td>Transmitter, Receiver</td>
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<td>SOS button</td>
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<td>GPS device, Mobile phone, Cloud server</td>
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<td>Location, orientation, speed</td>
<td>Cellular network</td>
<td>Mobile App.</td>
<td>GPS device, Mobile phone</td>
</tr>
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</table>

Table 3.6: Commercial Devices
3.8 Discussion

We want to analyze if the systems described above comply with the points that was revealed in user centric design studies we mentioned in chapter 2.

We notice, all solutions we discussed so far, requires a person with dementia (PWD) to carry a mobile device, may it be a mobile smart phone or a RFID tag, watch, shoe or bracelet. The mechanism of tracking would render useless if the device is not with PWD when wandering episode occurs. The concept relies on users memory and ability of independent living, which may not be dependable in case of PWD. Device maintenance is another issue that might prove to be cumbersome.

Trade off between privacy and safety, a discussion that came up in user studies described in chapter 2, is balanced in some systems using safe-zone alarms, where location data in transmitted to trusted caregiver only when PWD venture outside of pre-determined boundary, as opposed to track and store data continuously. Incidentally, the concepts of safe-zones and alert notifications have also been discussed in need-finding studies. Several systems integrate these ideas in their algorithms.

A simple user interface is desirable to ensure ease of use in emergency situations. Systems running there applications on smart phones with other software, in case of application malfunction or shut down, would be challenging if a manual restart is required. In contrast, at present, smart phones are pervasive, carried everywhere and less conspicuous; an additional device attached to a person may draw unwanted attention. Moreover, technologies to aid other dementia symptoms, if necessary, may have to be integrated into the same device or system ecology, increasing complexity. Dedicated buttons for issuing alerts are proposed by users, which is difficult to achieve in multi-purpose devices.

To increase independence in travel, navigational tools were suggested in user study,
for guiding a user to a destination. Several such system proposals were found during our survey mentioned in section 3.4.

Global Positioning System is the most prominent technology utilized to localize an individual, experiments, and evaluation proving it to be quite effective and adequately reliable in this domain. It is feasible in terms of availability, portability, and expense. The internet is a popular medium utilized for data transmission, followed by mobile network communication modules.

A single system, that takes into account various scenarios (i.e. both indoor and outdoor) or definitions of wandering would be complex to design and implement.

We need to remember that any technology employed, should be feasible to use in real life, especially for dementia patients. Here, the trade-off is between increasing privacy of the patient and reducing risks. It is crucial to maintain connectivity at most times and to ensure that the sensors are triggered by targeted behaviors without fail. Additionally, contingency plans should be in place to account for the failure of the primary technology. Patient needs to carry the equipment at all times for optimal result. Ensuring comfort and physical safety is of paramount importance. In human centered research, a really important consideration is to select a technology that does not hinder the safety and comfort of the patients.

We noticed a number of features mentioned in the user studies, are implemented in commercial devices, like alert buttons, safe-zones, longer battery life, etc.
4 Survey: Algorithms for Geographic Pattern Detection

In this chapter, we explore five algorithms formulated to detect the four geographical patterns proposed by Martino-Saltzman [45] (see chapter 2) and classify wandering behavior. The methodologies differ in terms of utilized technologies, collected data, experiment ecology, subjects and formulation of underlying algorithms. Moreover, we particularly notice redefinition of or deviation from the basic patterns to fit them in environmental setting or scenarios.

4.1 Temporal Episodic Approach

An ad-hoc algorithm was devised by Vuong et al. [95], to detect and automatically classify Martino-Saltzman [45] patterns (direct, pacing, lapping and random) in movement trajectories, based on the data set from [42] [28].

The input to the algorithm is pre-collected spatiotemporal data, where spatial data or locations are specific spots at an indoor environment and temporal data are time instance or time spent at each location. Prior to applying this algorithm, a preprocessing step should aggregate data points into discrete locations.

**Trajectory Segmentation** The complete spatial movement trajectory can be divided into episodes by time. Each episode consists of locomotion (time spent to move...
from a source location to a destination location) and non-locomotion (time spent at the destination location) phases. The goal of the algorithm is to classify these episodes into Martino-Saltzman [45] movement patterns - direct, random, lapping and pacing. The authors assumed, that time spent to move directly between pairs of consecutive locations are constant and could be set as hyper parameters of the algorithm. Moreover, they defined movement as moving from one location to an immediate next location. An episode is formed with one or more consecutive movements. The end location of one episode is the start location of the next episode. In an effort to determine the boundary or end point of an episode, the authors consulted medical research concerning wandering. They decided that a location is end point of an episode, if the duration of the episode exceeds 5.41 minutes at that location or time spent at a location is more than 15 seconds.

The authors redefined lapping and pacing patterns to include thresholds - a pacing episode should include at least three movements between same two locations, a lapping episode should include at least two circular movements among at least three locations. Considering all the previously mentioned assumptions, the authors formulated their algorithm (figure 4.1) using both spatial and temporal information. They mention using Longest repeated sub-string algorithms for detecting lapping episode.

**Experiment and Results** The algorithm was implemented in J2SE environment and evaluated on a subset (data from one subject only) of data set collected in [42]. Parameters (i.e. travel time between two locations) of the algorithm are set to specific values derived from data set. Among 74 recorded movement data, the algorithm detected 46 movement episodes and classified 9 as random, 2 as pacing, 1 as lapping and 34 as non-wandering direct pattern. The authors claimed their results are “consistent with” manually labelled ground truth data mentioned in [28], although
they did not present any formal values of evaluation (i.e. precision, recall). They specifically reported that the 1 lapping and 2 pacing patterns mirrors ground truth values.
4.2 $\theta_{WD}$ Algorithm: Utilization of Vector Angles

$\theta_{WD}$ algorithm proposed by Lin et al. [40] is a binary wandering trajectory classification algorithm designed for outdoor environment. They configured the algorithm considering the angle between two travel trajectories to detect wandering behavior. They considered only lapping and pacing patterns as indicators of wandering. They defined ‘sharp points’ as positions in the travel trajectory where the angle is at least 90 degrees. They also defined wandering as - “a loop-like travel, with each loop that consists of a series of trace segments, clamped by two adjacent sharp points within a given distance range.” The algorithm described in figure 4.2 aims to detect wandering patterns based on this definition. As a pre-processing step, the authors filtered noisy GPS points, setting a maximum distance threshold between adjacent location points (figure 4.3) and crowded points using mean shift cluster methods [21] (aggregate closely positioned locations within a radius into a single cluster center), which yields a series of cluster centers to feed to the algorithm (figure 4.4).

Experiment and Results They [40] evaluated their algorithm using three real world data sets. The data is collected using GPS equipped cell phones. Each data set contains more than hundred trajectories, collected over a period of seven days from several participants. They do not mention if the participants are dementia patients or healthy users mirroring wandering behavior. Nothing was mentioned about the participants i.e. people with dementia, or healthy users mirroring wandering behavior; however, each trajectory was manually labeled by the participant, and therefore it can be inferred that the participants were not suffering from dementia. These labels are considered as ground truth data for the experiment. Each data point is in the
Figure 4.2: Wandering Detection Algorithm proposed by Lin et al. [40]

format [latitude, longitude, time-stamp]. They used Area Under ROC Curve (AUC) to measure performance of the algorithm and reported a detection rate of 90 percent and false alarm rate of 5%.

Interesting enough, this algorithm failed to detect a circular trajectory, which resembles lapping movement, a significant wandering pattern. The authors claimed it was purposeful movement. The algorithm does not take into account any other sensory data that can verify a purposeful movement. Thus from only trajectory data
it should classify that pattern as wandering. In the smooth circular trajectory, there are gradual angular changes as opposed to sharp angular changes, based on which the algorithm is formulated.

They also provided a plot presenting computation time across increasing number of data points. Calculation time increases rather linearly with number of data points.
For 8000 trajectory points, the calculation time was .6 seconds. Intel Core E8400 PC with 2 GB RAM was used for calculation. The calculation was done offline in the remote PC. Hence, if turned into an online system, data transfer latency should also be considered.
4.3 Machine Learning Approaches and Deterministic Algorithm

Detecting geo-patterns in movement trajectories is also investigated in the work of Vuong et al. [91], with two different approaches. Time and location data utilized in both experiments are collected using RFID activity monitoring system, in a different study conducted in [42] [28]. Same data set was used in [95].

Deterministic Algorithm In one approach, Vuong et al. [91] formulated a deterministic algorithm that classifies snippets in travel episodes. Travel episodes, composed of a sequence of locations and defined by start and stop locations, are automatically segmented by a module that takes into account stopping threshold, maximum direct travel time, and wandering offset time. Here, locations in a trajectory represents discrete locations in a living facility as opposed to continuous location data. Extracted episodes are inputs to a deterministic tree-based algorithm, that detects the travel patterns contained in a particular episode. Three sub-modules are employed, to detect and mark direct, lapping, and pacing sub-sequences within an episode; any other sub-sequence is marked as random. Sub-modules of the algorithm can be visualized in figure 4.5 4.6, 4.7, 4.8, 4.9.

Machine Learning Approaches In a separate experiment, they employed eight machine learning algorithms - Naive Bayes, Multilayer Perceptron, Random Forest, Bagging, Support Vector Machine, K Nearest Neighbour, Logistic Regression, and Pruned Decision Tree (C4.5), in Weka environment, to classify episodes as direct, random, lapping or pacing. Entropy, number of repeated locations, number of repeated travel directions, and number of opposite travel direction pairs are used as
attributes.

**Experiment and Results**  Experimental results from [91] reveals, among the machine learning algorithms, Random forest yields best results with accuracy of 92.3 percent. Composed of ten decision trees, with a mode voting process, it is a more
Figure 4.6: *isDirect* Algorithm proposed by Vuong et al. [91]
complex method than single decision trees. The experiment utilized *leave one subject out* method - in each iteration, data from four participants were used for training, and one participant was used as testing data. The algorithms were judged based on
Figure 4.8: checkLapping Algorithm proposed by Vuong et al. [91]
sensitivity, specificity, precision, latency and F-1 measure.

The deterministic algorithm was applied to same data set, using 10 fold cross validation method, which improved recall by 5.9 percent to 98.2 percent and latency was reduced to .0003 seconds. This observed difference in recall and latency, between machine learning and deterministic approaches, were found statistically significant ($P < .01$). The authors pointed out some scenarios where deterministic algorithm fails to perform well. The algorithm, not being adaptive, fails to correctly recognize various forms of random patterns. Performance is improved if treated as a binary classifier, only differentiating between direct and non-direct patterns, as opposed to distinguishing among four patterns.

### 4.4 Patterns from Inertial Sensor Output

Vuong et. al. [93] addresses wandering behavior in indoor environment, also based on the four wandering patterns [45]. They use inertial sensors, to detect if a patient
is in locomotion and to distinguish the patterns in movement. APDM monitor is a wearable device that accommodates accelerometers, gyroscopes and magnetometers. The functionality of the accelerometer is utilized to calculate the translational acceleration of the patient to detect a movement. The magnetometer component is used to measure the orientation data of the patient. To detect if an individual has started moving, the transitional acceleration should exceed a threshold. To remove noise created by fluctuations, they use scalar quantization to clamp a range of angular values to discrete values.

In ideal cases, the system should output different types of orientation signals for the four patterns. The different output signal patterns are described in [93]. The direct movement pattern yields a constant signal. For random pattern, the signal changes randomly. If a person is pacing, there is a change in the signal by 180 degrees, approximating the movement when the person turns around. In between, where the person is walking straight, the signal remains somewhat constant. If the person continuous to pace, this pattern is repeated. When there is a lapping pattern in movement, the signal rises gradually from present value to 360 degrees and then sharply drops to 0 when a circle is complete. For lapping in the opposite direction, the signal drops to 0 gradually, and in circle completion, sharply increases to 360 degrees. For the last two patterns, the signals should repeat a sequence in the duration of wandering.

**Experiment and Results** The researchers [93] designed a well defined experiment to include data from both non-dementia and dementia participants. They conducted three experiments - a controlled experiment with non-dementia participants, an uncontrolled with non-dementia participants and an uncontrolled experiment with dementia patients. For uncontrolled experiments, ground truth labelling was done by
observation and recording participant movement. Controlled experiment with non-dementia participants yielded a recall of 100 percent with computation latency of .01 seconds. For uncontrolled experiment with non-dementia participants, they compared the results of their algorithm with two more algorithms that analyzes with time series data - Dynamic Time Warping and Symbolic Aggregate Approximation. Their proposed algorithm outperformed for all patient data in terms of recall and latency. Controlled experiment with dementia participants also yielded a recall of 100 percent with computation latency of .01 seconds.

### 4.5 Grid World Approach

Martino-Saltzman [45] movement patterns are also utilized, in formulating wandering detection algorithm, in the work of Kumar et al. [36]. With a goal to incorporate detection in both indoor and outdoor environment, they divide the physical space, where the movements or travels take place, into square grids. A grid unit can be accessed through one of the four edges perpendicularly only, not diagonally.

**Pattern Redefinition** The authors redefined the four movement patterns (direct, lapping, pacing, random) to make them fit into the grid representation of environment. They distinguish between direct and random patterns using sub-path intersections. In direct patterns, trajectory do not intersect within a grid, whereas in a random pattern there may or may not be intersections. Also direct pattern is more efficient than random pattern. In order to be considered as a lapping or a pacing pattern, the trajectory must contain at least two consecutive slightly overlapping cycles or loops. The area inside loops are smaller in pacing patterns than in lapping ones. If there is no overlapping area among the loops, or there is only one loop, the trajectory is then...
classified as random pattern.

**Trajectory Segmentation** The first phase of the algorithm deals with segmenting a trajectory into simpler sub-parts, to simplify representation and computations, an idea similar to [95]. First, a trajectory is divided into non-locomotion (no motion for more than sixty seconds) and locomotion segments. Each locomotion segment is an episode, that can be further divided into bursts or sub-trajectories, at locations where the direction of movement changes. Each burst holds spatial and temporal data to represent the episode. For example, the ith episode, \( E_i \), can be represented using a series of bursts, \( B_i = [x, y, \text{timestamp}] \), where \( x \) and \( y \) are location co-ordinates. So, \( E_i = B_1, B_2, ..., B_n \). Each burst is divided into equal length steps, length of which (step-length) is calculated using the vector angle or direction and length of the burst. Each step should only enable moving to one adjacent grid unit. A step is a vector of step-length at the direction of the burst it represents - \( S = \text{step} - \text{length}.d \). In this way, each episode can be represented with a series of steps - \( E_i = [\text{Stcord}_i, V_i, \text{Time}_i] \); where \( \text{Stcord}_i \) is start co-ordinate of the episode, \( V_i = [S_1, S_2, ..., S_m] \) and \( \text{Time}_i = [t_1, t_2, ..., t_m] \).

**Pattern Identification** These reformed episodes are then divided into looping (“longest continuous segment which intersect with itself”) and non-looping (“longest continuous segment which does not intersect with itself”) segments. According to the definitions previously mentioned, looping segments may be indicators of lapping, or maybe random patterns and non-looping segments represents direct or random patterns. The authors devised an algorithm to detect indices of the boundary steps of looping segments using summation of step-length (figure 4.10).

The next phase is to label non-looping segments to direct or random, which can
(a) Find Loop Index

Figure 4.10: Finding loop-index in an episode by Kumar et al. [36]
be judged using efficiency. Segment efficiency is calculated by - Optimal segment length / Actual segment length; where Actual segment length is scalar summation of all step-lengths within that segment and Optimal segment length is calculated using $A^*$ algorithm. The looping segments are then labelled lapping or pacing, if there are two or more consecutive, slightly overlapping loops. If enclosed area exceeds the minimum area possible with given segment length, indicates a lapping pattern.
**Experiment and Results** Evaluation of the grid-based algorithm [36] is more convincing. For both indoor and outdoor data, to reduce class imbalance (wandering episodes are scarce compared to normal movement), 25 episodes or trajectories are selected for each type of movement pattern. UWB data set (generated during a previous research by the same team of researchers) is used to evaluate performance in the indoor setting. Outdoor data is generated for this research by a non-dementia participant. Output of algorithm are compared to manually plotted ground truth label, to measure precision and recall. The experiment yielded overall accuracy of 90 percent.

### 4.6 Discussion

Experiments conducted for these researches requires user participation for data collection. Due to ethical constraints surrounding experiments involving human subjects, data are not publicly available. We notice that most experiments are conducted on data sets that are quite limited in size collected from a limited number of subjects. Therefore, it is possible that the results suffer from experimental setup biases and do not necessarily reflect real world scenarios. Moreover, comparison among different approaches and algorithms are not feasible as data, platform, environment, experiment design are quite different. For example, some algorithms are based on room to room movement where each room is treated as discrete point in trajectory [95] [91], whereas other algorithms consider consecutive co-ordinate in space, as discrete points in trajectory [40] [36].

Moreover, all algorithms are based on generic models of the aforementioned patterns. In reality, the patterns may vary depending on the person, differentiation between wandering and purposeful movements may not be so straightforward.
In the indoor setting, RFID sensor data (Cartesian space coordinates) are prevalent, whereas GPS data (Longitude, Latitude) is used in the outdoor experiments. A challenge is to seamlessly merge the two scenarios under one algorithm or system; for example, upon detection of home-zone, the indoor wandering detection sub-component would be turned on. The problem arises when person with dementia ventures into an unknown indoor environment. There, technology like RFID, with wall mounted sensors of limited range, will not be feasible. Again, GPS data is not precise enough to detect patterns in a confined, smaller area.
<table>
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<th>Data</th>
<th>Sensors</th>
<th>Algorithm</th>
<th>Study type</th>
<th>Evaluation</th>
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<td>RFID</td>
<td>Ad hoc (Repeated location count)</td>
<td>Clinical trial data set from [42], 1 participant</td>
<td>Classification and comparison with empirical results</td>
<td>consistent results</td>
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<td>[40]</td>
<td>2012</td>
<td>Outdoor</td>
<td>Sequence of locations (latitude, longitude, time-stamp)</td>
<td>GPS</td>
<td>Ad hoc (Episode Segmentation with Vector Angles)</td>
<td>User study (100 traces)</td>
<td>Area Under ROC Curve</td>
<td>90% detection rate, 5% false alarm rate</td>
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<td>[91]</td>
<td>2014</td>
<td>Indoor</td>
<td>Discrete locations, time</td>
<td>RFID</td>
<td>Machine learning and Ad hoc approaches</td>
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<td>Precision, recall, latency, specificity, F1 measure</td>
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<td>Recall, latency comparison with two algorithms</td>
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<td>RFID</td>
<td>Ad hoc (Grid, episode segmentation, travel efficiency, loop detection)</td>
<td>Clinical trial, 25 participants</td>
<td>Recall, precision</td>
<td>90% accuracy</td>
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Table 4.1: Algorithms for Geographical Pattern Identification
5  Analysis of Algorithm $\theta_{WD}$

Our research yielded comparatively fewer literature addressing geographical pattern detection. We described several algorithms, in chapter 4, built around this topic. We hypothesized this domain may have more correlation or consistency with actual wandering behavior, as the underlying idea flourished from direct medical research with dementia patients [45]. To perceive the significance of this under-explored sector, we selected the algorithm proposed by Lin et al. [40] (see chapter 4 section 4.2) for detail exploration; this approach utilizes basic vector mathematics, is flexible, and computationally efficient. Our aim was to search for techniques to extend its spectrum to accommodate indoor scenario along with outdoor ecology.

In this chapter, we analyze the aforementioned algorithm, introduce an additional feature, and examine the effectiveness of the feature in differentiating various wandering patterns. Besides, infrared motion sensor camera, a relatively unexplored technology in this domain, is reviewed to determine its applicability in wandering management.

5.1  Algorithm

Lin et al. [40] formulated an algorithm $\theta_{WD}$ to detect wandering segments in movement traces. Although the algorithm is devised for outdoor scenarios based on a sequence of GPS location data (longitude, latitude), the authors utilized Martino–Saltzman [45] movement patterns, which is derived from indoor travel trajectories of dementia
patients (see chapter 2), in phrasing a new definition of wandering. Direct pattern is purposeful non-wandering travel, whereas Random, Lapping and Pacing are patterns representing probable wandering behavior. Instead of detecting the aforementioned four patterns, this algorithm attempts to identify only if a trajectory contains loops, and uses the patterns to achieve a more generalized solution.

The authors hypothesized that, in a wandering trajectory, there are points (referred to as sharp points) with prominent changes of direction, amounting to vector angles (section 5.3) of equal to or more than 90 degrees. Therefore, a travel trajectory contains wandering episodes or segments which consist of a sequence of sharp points, each of which is situated within a distance threshold of it’s neighboring sharp points. Continuous sharp points create at least one loop in travel trajectory.

According to the authors, the lapping pattern consists of three or four sharp points. They depicted this pattern as having triangular, rectangular or a closed random shape, encompassing an area in a loop-like manner. Pacing pattern forms sharp points where the change of direction is almost 180 degrees and travel is in areas approximately between two points. In both cases, a sequence of sharp points will be formed.

Figure 5.1 illustrates $\theta_{WD}$ algorithm. The pre-processing process replaces points clustered together with single cluster center points. $\theta_{WD}$ algorithm takes as input a sequence of such points. Thus, the aim of this algorithm is to identify if a movement trajectory can be labeled as wandering. As mentioned before, a movement trajectory with at least one loop is considered wandering. The authors decided a loop is formed by at least four consecutive segments, each with a length of at most 100 meters; each segment has sharp points at both ends. If a sub-trajectory meets all the constraints, it is marked as a wandering trace. The algorithm also counts the number of wandering traces in the complete movement trajectory.
5.2 Observations

The algorithm does not take into consideration direct and random patterns and their features that may help differentiate wandering from non-wandering.

However, they regard a circular loop as purposeful behavior, which contradicts the original definition of a lapping pattern. Loop-like movements with definite sharp
points (i.e. triangular, rectangular or other polygons with angles more than 90 degrees) are only considered for lapping pattern. Even triangular trajectory, with the exception of a right-angle triangle, would not produce sharp points detected by the algorithm. Any circular, semi-circular or even elliptical trajectory would create gradual changes in direction, with vector angles less than 90 degrees, which will not be detected by the algorithm as wandering behavior.

Procedures in determining distance thresholds, cluster radius in the preprocessing step and wandering segment length, in an indoor environment may diverge from features considered in an outdoor ecology, where the perimeter is considerably larger, thus impact of trajectory distortion, influenced by obstacles created by environmental elements, is less. In a smaller environment, thresholds are subject to change depending on the structure of different residence. Moreover, it may differ at various locations within one residence. Therefore, customizable thresholds may be feasible in indoor scenarios. Therefore, a 100 meters distance threshold will not be feasible in an indoor environment.

The algorithm is built in such a way that only one loop, with four segments divided by sharp points, are enough to detect a wandering trace. According to the original definition of the patterns, repetitive loops are required to label a trace as wandering.

### 5.3 Vector Angles

In an attempt to identify differential features among the four patterns, we considered extracting spatial orientation data from collected space-time data. A vector can be formed using two consecutive data points. The angle between two such consecutive vectors (from three consecutive data points) is an indicator of the direction of movement. This approach is employed in [40], on GPS location data collected for
outdoor experiments.

In two-dimensional euclidean space, a vector \( \vec{u} \), with respect to an origin, can be represented with \( u_x \) and \( u_y \) as it’s scalar components - \( \vec{u} = (u_x, u_y) \).

The dot product of two vectors \( \vec{u} = (u_x, u_y) \) and \( \vec{v} = (v_x, v_y) \) can be computed from equation 5.1.

\[
\vec{u} \cdot \vec{v} = \|u\| \|v\| \cos \theta \quad (5.1)
\]

Here, \( \theta \) is the angle between \( \vec{u} \) and \( \vec{v} \). \( \|u\| \) and \( \|v\| \) are lengths of \( \vec{u} \) and \( \vec{v} \) respectively.

\[
\|u\| = \sqrt{u_x^2 + u_y^2} \quad (5.2)
\]
\[
\|v\| = \sqrt{v_x^2 + v_y^2} \quad (5.3)
\]

The dot product can also be calculated directly from it’s scalar components.

\[
\vec{u} \cdot \vec{v} = u_x v_x + u_y v_y \quad (5.4)
\]

From equation 5.1 and 5.4, the angle between \( \vec{u} = (u_x, u_y) \) and \( \vec{v} = (v_x, v_y) \) can be calculated.

\[
\|u\| \|v\| \cos \theta = u_x v_x + u_y v_y \quad (5.5)
\]
\[
\theta = \cos^{-1}\frac{u_x v_x + u_y v_y}{\|u\| \|v\|} \quad (5.6)
\]
\[
\theta = \cos^{-1}\frac{u_x v_x + u_y v_y}{\sqrt{u_x^2 + u_y^2} \sqrt{v_x^2 + v_y^2}} \quad (5.7)
\]

A location data point, in a two dimensional space represented by Cartesian coordinate system, with respect to a fixed origin, can be depicted as \( L = (x, y) \),
where \(x\) and \(y\) are the co-ordinates along x-axis and y-axis respectively. A vector can be formulated, using two location data points \(L_1 = (x_1, y_1)\) and \(L_2 = (x_2, y_2)\), as \(\overrightarrow{L_1L_2}\), with its direction pointing from \(L_1\) to \(L_2\).

For three consecutive data points \(L_{i-1} = (x_{i-1}, y_{i-1})\), \(L_i = (x_i, y_i)\) and \(L_{i+1} = (x_{i+1}, y_{i+1})\), vectors \(\overrightarrow{L_{i-1}L_i}\) and \(\overrightarrow{L_iL_{i+1}}\) can be formed.

\[
\overrightarrow{L_{i-1}L_i} = (x_i - x_{i-1}, y_i - y_{i-1}) \quad (5.8)
\]
\[
\overrightarrow{L_iL_{i+1}} = (x_{i+1} - x_i, y_{i+1} - y_i) \quad (5.9)
\]

Angle between the vectors can be calculated using equation 5.5.

\[
\theta = \cos^{-1} \frac{(x_i - x_{i-1})(x_{i+1} - x_i) + (y_i - y_{i-1})(y_{i+1} - y_i)}{\sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2} \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2}} \quad (5.10)
\]

### 5.4 Rate of Angle Change

Given four consecutive data points, two consecutive vector angles can be calculated using equation 5.10.

Let us assume, \(L_i, L_{i+1}, L_{i+2},\) and \(L_{i+3}\) are four consecutive data points at times \(t_i, t_{i+1}, t_{i+2},\) and \(t_{i+3}\) respectively, from a sequence of \(N\) data points \(L_1, ..., L_i, L_{i+1}, L_{i+2}, L_{i+3}, ..., L_N\) aligned to time sequence \(t_1, ..., t_i, t_{i+1}, t_{i+2}, t_{i+3}, ..., t_N\). Vector angle \(\theta_i\) can be calculated putting values from data points \(L_i, L_{i+1}\) and \(L_{i+2}\) in equations 5.8 - 5.10. Similarly, \(\theta_{i+1}\) can be derived from points \(L_{i+1}, L_{i+2},\) and \(L_{i+3}\).

The rate of change of angles aligned to time \(t_i\) is calculated using equation 5.11.

\[
\delta_i = \frac{\theta_{i+1} - \theta_i}{t_{i+1} - t_i} \quad (5.11)
\]

110
If $\theta_1$ is the vector angle between $V_1$ and $V_2$ at time $t_1$, $\theta_2$ is the vector angle between $V_2$ and $V_3$ at $t_2$, then rate of angle change is calculated by -

$$\delta_1 = \frac{\theta_2 - \theta_1}{t_2 - t_1}$$

5.5 Movement Data Collection with Infrared Motion Tracker

We chose the OptiTrack optical motion capture system [62] to observe the outcome of employing infrared sensors to collect travel data in an indoor environment.

5.5.1 Equipment Overview

OptiTrack system consists of cameras, with infrared (IR) sensors, which can be placed around the environment where movement or motion experiments take place. The cameras are also capable of producing infrared light. IR filters detect only light from the infrared spectrum and nullify any other light. The cameras are connected to a desktop computer through an Ethernet switch by Ethernet network cables (maximum 100 meters). The motion sensor network transmits real-time motion or movement data through this wired connection. A system architecture is depicted in figure 5.2 collected from OptiTrack website [70]. The software platform, that works as an interface for users to configure the entire motion capture system, collect and process (record, edit or export) data, is Motive [55].

Markers Markers [44] are attached to objects (i.e. a piece of clothing an individual is wearing) to identify them and track their positions by the motion capture system. There are two types of markers - active and passive. Active markers have LED lights
Figure 5.2: OptiTrack Ethernet Camera System [70]

and power source to emit their own infrared light and are synchronized using radio frequency signal. Passive markers with retro-reflective surface, having no power source or illumination capability, are only capable of reflecting infrared light (IR) back to its source with minimum scatter. In this scenario, each motion capture camera emits infrared light, which, in turn, is reflected by the passive markers at the direction of its source camera, and then detected by camera’s infrared sensor. This data is used to calculate the position of the marker in a 2D environment and, in turn, in a 3D
environment.

**Signal Interpretation** 3D coordinate data is constructed from multiple 2D images of a marker, captured by multiple cameras at the same time instance, from different vantage points. The captured data represents a 3D capture volume and the process is called reconstruction. “Reconstruction in motion capture is a process of deriving 3D points from 2D coordinate information obtained from captured images” [9]. Subsequently, a series of 3D position and orientation information of the tracked object is extracted from raw data.

**Calibration** To configure Motive for data capture, it is adjusted to the external environment, where data capture should take place, by Calibration. The goal of calibration is to determine position and orientation of each camera in the network and produce a 3D capture volume, along with bias or systematic error introduced in data. Detail steps of the calibration process are described in [17]. An origin and a ground plane are also set, to configure the 3D coordinate space and axis alignments, at the end of the calibration process.

### 5.5.2 Discussion

The calibration process introduces a potential disadvantage of using this motion capture system in real-world scenarios. Calibration should be carried out each time there is a change in the camera network, or periodically to accommodate changes due to environmental factors, to accurately interpret subsequent data. It requires physically waving a piece of equipment (referred to as wandling) across the volume of space. Periodical calibration may be cumbersome for non-technical end users.

Passive markers are required to be adequately visible (specifically the retro-reflective
surface) by the cameras and, strategically placed, to be successfully detected and to subsequently produce a sequence of good quality movement data. Also, the cameras detect infrared ray created or reflected from any source. Any retro-reflective surface, other than the selected markers, should be removed or covered to reduce interference. In a residential environment, with personal daily use objects and furniture required to be available in the living space, these restrictions are not achievable to this extent.

The equipment are expensive, even marker materials; considering installations and maintenance, promoting widespread use would be demanding.

On the positive side, this technology is unobtrusive and will not create any physical harm or side effects. Passive markers are wireless, lightweight and smaller in size, making them ideal as wearable sensors in addition to infusing them in daily activities unnoticeable. With minimal pre-processing, the collected data is precise and captures the subtle difference in movement, lowering false negative in detection. The cameras do not capture images that can be used to recognize individuals or their surroundings, ensuring privacy.

5.6 Description of Collected Data

Data from a session could be saved in a comma delimited .CSV file. Each file has seven rows of header data at the top. Original space-time data starts from eigth row; Sixth and seventh row contain attribute labels.

Each row has sixteen columns among which ten contains data and rest are empty. From left to right, columns represent frame number, time in seconds, rotation x coordinate, rotation y coordinate, rotation z coordinate, position x coordinate, position y coordinate, position z coordinate and Error Per Marker (table 5.1). For our study, we need frame number, time in seconds, position x coordinate, and position z coordinate.
ordinate. Rest of the data is discarded during preprocessing step. At the origin, x-axis and z-axis are aligned parallel to the ground, and y-axis is aligned perpendicular to ground. Therefore, position x coordinates, and position z coordinates represent movement data across the ground level or floor.

<table>
<thead>
<tr>
<th>Frame</th>
<th>Time</th>
<th>X</th>
<th>Y</th>
<th>Z</th>
<th>W</th>
<th>X</th>
<th>Y</th>
<th>Z</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>0.007677</td>
<td>0.014435</td>
<td>-0.00225</td>
<td>-0.999864</td>
<td>-2.041308</td>
<td>0.740586</td>
<td>1.913831</td>
</tr>
<tr>
<td>1</td>
<td>0.008333</td>
<td>0.007693</td>
<td>0.014539</td>
<td>-0.002279</td>
<td>-0.999862</td>
<td>-2.041301</td>
<td>0.740584</td>
<td>1.91383</td>
</tr>
<tr>
<td>2</td>
<td>0.016667</td>
<td>0.007701</td>
<td>0.01454</td>
<td>-0.002306</td>
<td>-0.999862</td>
<td>-2.041311</td>
<td>0.740597</td>
<td>1.91382</td>
</tr>
</tbody>
</table>

Table 5.1: Data Example

The first row contains comma separated label and value pairs containing relevant information about a session. Labels are format version, name of file, captured frame rate, transmitted frame rate, start time of session, total number of captured frames, total number of transmitted frames, rotation type, unit of length, and co-ordinate space type. An example of this information is depicted in table 5.2.

<table>
<thead>
<tr>
<th>Label</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Format Version</td>
<td>1.21</td>
</tr>
<tr>
<td>Take Name</td>
<td>Session_10</td>
</tr>
<tr>
<td>Capture Frame Rate</td>
<td>120</td>
</tr>
<tr>
<td>Export Frame Rate</td>
<td>120</td>
</tr>
<tr>
<td>Capture Start Time</td>
<td>2017-09-15 02:50.17PM</td>
</tr>
<tr>
<td>Total Frames in Take</td>
<td>7978</td>
</tr>
<tr>
<td>Total Exported Frames</td>
<td>7978</td>
</tr>
<tr>
<td>Rotation Type</td>
<td>Quaternion</td>
</tr>
<tr>
<td>Length Units</td>
<td>Meters</td>
</tr>
<tr>
<td>Coordinate Space</td>
<td>Global</td>
</tr>
</tbody>
</table>

Table 5.2: Data Header Example
A detail formal description of data exported to .CSV file is illustrated in [23].

**Data Preprocessing**  As mentioned before, several columns are removed from the data frame as they do not contain information relevant to our experiment. Only columns containing frame number, time in seconds, x coordinate of position in 3D space, and z coordinate of position in 3D space is retained.

When analyzing data, we encountered that, at some places, coordinates continuously increases and decreases at very small variations. These are interpreted as direction change, vector angles being close to \(180^\circ\), although original movement is only in one direction. The reason for this noise may be due to relative placements of sensor and markers, and overlapping data from several cameras creating a to-and-fro pattern.

<table>
<thead>
<tr>
<th>Frame</th>
<th>X</th>
<th>Z</th>
<th>Vector angle</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>−2.410669</td>
<td>2.123059</td>
<td>−</td>
</tr>
<tr>
<td>1</td>
<td>−2.410754</td>
<td>2.123153</td>
<td>increase 178.256052°</td>
</tr>
<tr>
<td>2</td>
<td>−2.410655</td>
<td>2.123050</td>
<td>decrease 177.938484°</td>
</tr>
<tr>
<td>3</td>
<td>−2.410748</td>
<td>2.123154</td>
<td>increase 177.249075°</td>
</tr>
<tr>
<td>4</td>
<td>−2.410662</td>
<td>2.123048</td>
<td>decrease 179.675786°</td>
</tr>
</tbody>
</table>

Table 5.3: Data Noise Example

To remove nuance irregularities, we applied moving average as a smoothing technique, using a rolling window size of 500. After smoothing, data is re-sampled using 60 seconds fixed interval rule and mean value was taken to assign a value to that interval.
5.7 Analysis

Example of collected data, mirroring the four movement patterns, is plotted in figure 5.3. It is noticeable that smoothing as a preprocessing step may result in a certain amount of data loss. Preprocessing parameters may be determined upon examining a larger data set to avoid overfitting.

Vector angles across time are plotted in figure 5.4 for all four patterns. For direct walk, vector angles remain close to zero when the person is walking straight. There are significant changes in angles consistent with direction change. For random movement, there are sharp angle changes, but there are no rhythm or pattern in the changes. For lapping, the angles range from approximately 20 to 60. Here the changes are somewhat gradual rather than sharp. There is no significant pattern observed. For pacing, the angle changes sharply from 0 to above 90 and then drops again. There is a rhythm or repetitive pattern.

Figure 5.5 illustrates, in a three dimensional plot, the vector angles at each point of trajectory, at the direction of vertical Z axes. For pacing pattern, vector angles increase to higher values at the endpoints, where the direction of trajectory changes to the opposite direction. Angles between those two end points are of relatively lower values, approximately constant within a range. Thus, pacing could yield a rhythmic pattern in vector angle sequence. For direct pattern, there are only two points with a prominent abrupt direction change, and the vector angles rise up to almost 90 degrees, whereas straight walking results in a sequence of 0 degree vector angles. For lapping patterns, roughly straight trajectory and gradual change in direction produce lower valued vector angles, ranging from 20 to 30 degrees. Random walking does not produce a repetitive rhythmic pattern, and a series of higher valued angles could be found separated by a sequence of lower valued angles.
Figure 5.3: Movement Pattern Plots
We hypothesized that the rate of change of angles ($\delta$) between adjacent points in the travel data can distinguish travel patterns. In order to analyze the contribution of vector angles in distinguishing movement patterns, we examined if the rate of change of angles may be utilized as a feature, aggregated to vector angles. After analysis, we concluded that it has a linear relationship with vector angles, and therefore does not contribute to improvement in classification.

The rate of change of angles across time is plotted in figure 5.5. For a direct walk, $\delta$ remain close to zero when the person is walking straight. For random movement, $\delta$ bounces between negative and positive values without following any rhythm or pattern. For lapping, $\delta$ remain close to zero when the person is walking in a circle. The range of change is $-20$ to $+15$. For pacing, $\delta$ rises sharply from negative to 0,
stays constant and then rises to positive before sharply falling to a negative value again. There is a repetitive pattern or rhythm. The range of change is $-150$ to $+150$.

### 5.8 User study design

As our data collection procedure requires human participation, we had to procure an approval from Internal Review Board for user study and it was approved being not identified as human subject research. We aim to recruit participants with normal cognitive abilities. In participant consent form, we informed that the study’s intent is to formulate an algorithm to identify the four patterns in movement trajectory. Stating the experimental procedure and data collection method, we mentioned that,
Figure 5.6: Rate of change of angle

neither the technology used to collect data nor the walking required for experiments, exposes the participants to any risk. The participants could discontinue the study at any time. Also, data is unidentifiable and any personal information cannot be inferred from them.

**Sensor Installation** The precision position tracker system *OptiTrack* is installed in the laboratory environment where the data collection would take place. Eight *OptiTrack cameras* are wall mounted around the laboratory area, which is an approximately 21ft x 33ft rectangular room, with an empty flat space at the center to conduct motion capture based experiments. The sensor network transmits data to a desktop computer, placed inside the laboratory, running *Motive* software.
**Wearable Marker Placement**  On the outside surface of a hat, we will attach passive markers, which are tracked by the infrared sensors. The user will wear the hat while participating in the experiments. The markers are very small (about 5 cm in diameter) and should not create any discomfort (i.e. due to weight) to the participant.

**Controlled Experiment**  In controlled experiments, the participants will be asked to replicate the four movement patterns mentioned in [46] - direct, random, lapping, and pacing, one by one, each pattern for one minute.

**Uncontrolled Experiment**  In an uncontrolled experiment, the participants will be asked to move around the space for at least three minutes and include at least two of the four aforementioned patterns in their trajectories. The participant will not let the researchers know which patterns will be included.

**Challenges**  Some challenges associated with research in this domain are -

- Lack of freely distributed data corpus from actual clinical experiments.

- All assumptions are based on medical literature, not from real life experiments.

- Limited existing research merging medical research and technological interventions.

- Implemented system and employed technology should accommodate affordability, usability with effectiveness.
6 Conclusions

With the ever growing rate of dementia patients, it is imperative to have automated technological systems to increase independence in daily living and reduce accidents and stress. Wandering, being a pervasive behavior in persons with dementia, may result in unpredictable, insecure situations. We set out to address this problem, assembled literature to understand wandering behavior and how technology can assist in managing this behavior. Our survey revealed systems can be classified according to the perception of wandering, environmental setting, and underlying algorithms. Researchers integrate existing sensor, communication, hardware, and software technology to model a solution suitable for wandering behavior identification, as well as the issuance of notification and intervention. Several studies attempt to formulate algorithms to identify patterns in movement trajectories. While some components of proposed systems are parallel to results from need-finding user studies, there are areas where human computer interaction based research would help in developing user and domain centering features. Additionally, we attempted to analyze an algorithm built for detecting geographical patterns outdoor GPS movement data. With data collected using infrared sensors, we observed some limitations in this algorithm for employment in indoor settings. Infrared motion sensor cameras, although unobtrusive and health friendly, could be expensive, with complicated maintenance requirements, for practical use in this domain.
**Future Work**  Taking into account the importance of an automated solution, we aim to devise an efficient algorithm for detecting wandering tendencies of dementia patients in the indoor setting. Vuong et al. [91] formulated a deterministic algorithm for wandering pattern recognition in movement data collected using RFID tags. They demonstrated that machine learning and Ad-hoc deterministic algorithm, based on Martino-Saltzman patterns[46], are effective in identifying wandering behavior in certain environment. Their algorithm works with location-point based discrete data rather than continuous data. Our preliminary plan is to analyze continuous movement data collected using infrared sensors and use our knowledge in proposing new features in detection algorithms. Data would be collected in a laboratory setting imitating the wandering patterns of individuals affected with dementia, following procedures mentioned in IRB form (see A). We hope our research would assist in evaluating how well machine learning algorithms and deterministic algorithms perform on spatiotemporal data in the domain of movement pattern detection of dementia patients.
References


[38] L. Liao, D. J. Patterson, D. Fox, and H. Kautz. “Learning and inferring transportation routines”. In: *Artificial Intelligence* 171.5-6 (2007), pp. 311–331 (cit. on p. 9).


[76] F. Rudzicz, R. Wang, M. Begum, and A. Mihailidis. “Speech Interaction with Personal Assistive Robots Supporting Aging at Home for Individuals with...


A Appendix A

A.1 Institutional Review Board (IRB) Human Research Determination Form

Following are the information provided in the IRB Human Research Determination Form to receive an approval for conducting user study.

A.1.1 Purpose of User Study

Our Goal is to study existing algorithms, design new features to improve these algorithms, and eventually formulate a new, robust algorithm to classify travel patterns in the movement data of dementia patients and detect wandering behaviors.

From previous studies, researchers have identified four movement patterns in trajectories of a dementia patient.

**Direct** Travel from one location to another without diversion with definite purpose

**Random** Haphazard travel to many locations within an area without definite purpose

**Lapping** Repetitive circular movement in an area

**Pacing** Repetitive back and forth movement within limited area
Among these, random, lapping and pacing patterns are considered wandering behavior.

Our aim is to distinguish the last three patterns from direct, purposeful movement to detect wandering behavior. In order to formulate an algorithm for wandering detection and subsequently evaluate it, we require user generated data. Results from user study would establish empirical credence of our research. We hypothesize that data generated from human subjects not diagnosed with cognitive impairment would be sufficient for first stage of the study.

A.1.2 Procedures

We will need human participants to generate movement data. A prospective participant will be given a consent form which will depict detail information regarding the experiment. If the individual agrees to carry on with the experiment he would have to sign the form.

Participant recruitment  At this preliminary stage, individuals with normal cognitive ability and not suffering from dementia would be recruited to participate in the user study.

Inclusion criteria for recruitment  The participant should be of age 18 or more. He or she should be able to walk around the laboratory space without the help of any aid. It is imperative that they do not have walking impairment and heart disease.

Exclusion criteria for recruitment  Individuals can not suffer from a heart condition in order to participate in this study. Participants should not have a disability that may interfere with their locomotion during the study and put them at risk.
Experimental design  We will conduct the experiment in two sub parts.

1. First the user will be asked to move around the space and include at least two of the patterns. They will not let us know what pattern they will include in their trajectory.

2. For the next sub-part participants will be requested to emulate the four distinct patterns we aim to detect in a trajectory. They will be requested to simulate each pattern for two minutes. They are free to deny participation if they are not comfortable with any of the patterns and they will be requested to only simulate the other patterns they are comfortable with.

Risk  There are no risks associated with the speed or style of walking during the experiment. We expect the participant to walk as they would any other time. The laboratory space do not have any obstacles or elevation that would create a chance for accidents or injuries during movement. The participants do not need to wear any intrusive technology that would hinder their sight or hearing. Overall, we do not anticipate any physical or psychological risks of participating in this study.

A.1.3  Data and/or specimens

Data and/or Specimen Collection and Analysis

To summarize, our data comprises of spatial coordinates and time in seconds. This represents the position of an individual in the experimental setting (specifically laboratory space) at a specific time (in second). Time recorded is independent of actual date and time when the experiment will take place. The calculation of time will start from 0 when the recording of data starts for that particular session.
Data from a session will be saved in a comma delimited .csv file. Each file has seven rows of header data at the top. Original space-time data starts from eighth row. Sixth and seventh row contains attribute labels. Each row has sixteen columns among which ten contains data and rest are empty. From left to right, columns represent frame number, time in seconds, rotation x coordinate, rotation y coordinate, rotation z coordinate, position x coordinate, position y coordinate, position z coordinate and Error Per Marker. First row contains comma separated label and value pairs containing relevant information about a session. Sensors will pick up following information in each session: format version, name of file, captured frame rate, transmitted frame rate, start time of session, total number of captured frames, total number of transmitted frames, rotation type, unit of length and co-ordinate space type. Among these, columns containing frame number, time in seconds, x coordinate of position in 3D space, and z coordinate of position in 3D space will be retained. The remaining columns will be removed from data frame as they do not contain information relevant to our experiment.

Data and/or Specimen Collection Method

We will collect data by conducting user experiment in the laboratory environment.

Description of laboratory and equipments Data will be collected in SIVE (Simulation and Interaction in Virtual Environments) lab. It is located in University of Minnesota Duluth campus and is affiliated with computer science department. It is a 21ft x 33ft room with a large empty flat space at the center, surrounded by desks and computing devices placed near the walls. The laboratory is used to conduct research concerning user interaction with simulated virtual 3D environment. There are wall mounted Precision Position Tracker system (OptiTrack), which utilizes
infrared sensor technology, to track movements of users inside the lab space. We will utilize this tracker system to collect data for our study.

We will attach reflectors, that the infrared sensors detect and track to collect data, on a hat. The user will wear the hat while participating in the experiment. The reflectors are very small (about 5 cm diameter) and can be attached on the visible surface of a piece of clothing an individual is wearing without creating any discomfort. This technology is unobtrusive and will not create any physical harm or side effects. Movement data will be transmitted directly to a desktop computer from the wall mounted sensors and saved in .csv files.

**Identifiability of Data or Specimens**

All data collected will be de-identifiable. Data collected for this study will not be linked to individuals. There would be no ID associated with data that might be used to identify the person who contributed in generating the data. The consent form that a participant signs, will not be connected to the generated data and will be preserved separately for up to two years.
A.2 Consent Form for User Study

We would like to invite you to participate in a user study for a research project about detecting predefined patterns in movement data of individuals. This study is a precursor to a clinical study where the participants will be individuals affected with dementia. Please read this form and sign in the designated space if you agree to take part. You can ask any questions you may have regarding the study before signing this consent form.

Research Description

We are attempting to identify wandering patterns in the movement trajectory of a dementia patient. In this particular user study, we are replicating the wandering movement trajectories with the help of voluntary participation of individuals who do not suffer from dementia. In previous studies, four geographical patterns were identified in movement data of dementia patients. Our research focus is detecting these four patterns.

**Direct**  Travel from one location to another without diversion with definite purpose

**Random**  Haphazard travel to many locations within an area without definite purpose

**Lapping**  Repetitive circular movement in an area

**Pacing**  Repetitive back and forth movement within limited area

We hypothesize that data generated from human subjects not diagnosed with cognitive impairment would be sufficient for this stage of the study.
Voluntary Participation

Your participation in the study is completely voluntary. You can deny to participate in this study after reading the consent form or choose to stop participation at any time during the experiment.

Withdrawal from study

- If you first agree to participate but decide to discontinue in the middle of the study, you are free to withdraw your consent and discontinue your participation at any time.

- You are free to skip any sub-part of the study. If you feel discomfort during any part of the study please notify the investigator. You will be able to leave the study site immediately.

Duration of study

This procedure is expected to take approximately thirty minutes.

Procedure/Protocol

You will be asked to walk inside a laboratory space following certain patterns. We will record your movement data (position with respect to time) via infrared sensors and a personal computer.

We will conduct the experiment in two sub parts.

1. First you will be asked to move around the space for at least three minutes and include at least two of the four aforementioned patterns in your trajectory. You will not let us know what pattern you will include in your trajectory.
2. For the next sub-part, you will be requested to simulate the four distinct patterns one by one, each pattern for one minute.

If you are not comfortable with any one of the patterns, you are free to skip it and generate the other patterns. After a short break, you will be asked to repeat the second sub-part to generate another set of data.

**Data storage**

Data will be collected using infrared camera sensors and automatically transmitted to a lab computer.

**Risks**

- You will be asked to walk around inside a limited laboratory space. The laboratory has no windows. We suggest you do not take part if you are claustrophobic.

- Part of the experiment would require you to walk around in circular pattern. If you suffer from vertigo we suggest you not participate in that particular sub part.

- There are no risks associated with the speed or style of walking during the experiment. We expect you to walk as you would any other time. We do not anticipate any risks to you participating in this study. However, if you feel any discomfort (dizziness or exhaustion) and do not want to continue, you can stop any time you want.

- There is no known risk associated with using infrared sensors.
Benefits

There are no benefits for you from this experiment. However, results from this research could be beneficial for people suffering from dementia who exhibit wandering behavior.

Compensation

You will not receive compensation of any kind for participating in this study.

Privacy and confidentiality

Your identity will not be revealed or be associated with the recorded movement data. If the data or analysis report is made public, we will not include any information that will make it possible to identify you. You will be consciously emulating movement scenarios. Data will not mirror your personal movement patterns from daily life. So there is no risk of identifying your personal walking patterns or gait signature from the data.

Researchers

The study is conducted by Arshia Zernab Hassan under supervision of Dr. Arshia Khan of Department of Computer Science, University of Minnesota Duluth. If you have any questions after participating in the experiment please contact Arshia Zernab Hassan at hasa418@d.umn.edu and Dr. Arshia Khan at akhan@d.umn.edu.

Consent Form

I have read the above information, and have received answers to any questions I asked. I consent to take part in the study.
In addition to agreeing to participate, I also consent to having the movement data recorded and this form be kept by the researcher for at least three years beyond the end of the study.

Person obtaining consent

Signature

Date

Printed name
A Appendix B

A.1 Python Codes for algorithm $\theta_{WD}$

```python
import pandas as pd

""
#Function name: read_header_from_CSV
#Author: Arshia Zernab Hassan
#Function description:
Extract session variables and values from the first row of .CSV data file
to a dictionary
#Input Parameters:
1. Data file path
#Return:
1. A dictionary data type with –
   keys: session variables
   values: session values
#pre-condition:
   1. file path is valid

Sample session info row:
Format Version,1.21,Take Name,session,Pacing,Capture Frame Rate,120,
Export Frame Rate,120,Capture Start Time,2017-09-15 02.50.17 PM,
Total Frames in Take,7978,Total Exported Frames,7978,Rotation
```
**Type, Quaternion, Length Units, Meters, Coordinate Space, Global**

Sample Dictionary:

```
{
    'Capture Frame Rate': 120,
    'Capture Start Time': '2017-09-15 02.50.17 PM',
    'Coordinate Space': 'Global',
    'Export Frame Rate': 120,
    'Format Version': 1.21,
    'Length Units': 'Meters',
    'Rotation Type': 'Quaternion',
    'Take Name': 'session_Pacing',
    'Total Exported Frames': 7978,
    'Total Frames in Take': 7978
}
```

```python
def read_header_from_CSV(filepath):
    # Read first row of data (session info row)
    df = pd.read_csv(filepath, sep=' ', nrows=1, header=None).dropna()
    # Get number of columns (parameters and parameter value)
    no_of_columns = df.shape[1]
    # Extract session variables and corresponding value to dictionary
    parameters = dict()
    for i in range(0, no_of_columns, 2):
        parameters[df.loc[0][i]] = df.loc[0][i+1]
    return parameters
```

# Function name: read_data_from_CSV
# Author: Arshia Zernab Hassan
# Function description:
# Extract sequence of time and location data from .CSV data file
to a dictionary
# Input Parameters:
1. Data file path

#Return:

1. Data frame containing movement data

#pre-condition:

1. file path is valid

Sample extracted header of data file:

Frame, Time, X.1, Z.1

Sample rows of data file:

0.0.000000, -2.041308, 1.913831
1.0.008333, -2.041301, 1.913830

```python
def read_data_from_csv(filepath):
    #column numbers to extract
    cols = [0, 1, 6, 8]
    #read csv
    #comma(,) delimited
    #read only selected columns (0=Frame, 1=Time, 6=X.1, 8=Z.1)
    #header is at row 6, do not read previous rows (0-5)
    #Do not skip blank lines while reading
    #Drop rows with NA values
    df = pd.read_csv(filepath, sep=' ', usecols=cols, header=6,
                      skip_blank_lines=False).dropna()
    return df
```

Listing A.1: Read .CSV data file (read_data.py)

```python
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import math
```
#Function name : preprocess
#Author : Arshia Zernab Hassan
#Function description :
Apply pre-processing steps to time-stamp coordinate Data Frame
#Input Parameters :
1. Pandas Data Frame
Sample header of input data frame :
```
Frame Time X.1 Z.1
```
Sample rows of input data frame
```
0 0.000000 -2.041308 1.913831
1 0.008333 -2.041301 1.913830
```
#Return :
1. Data frame after pre-processing
#pre-condition :
1. data frame has valid value

```python
def preprocess(df):
    #Average rolling window of 500 data points
    df = df.rolling(window=500).mean().dropna()
    #Add index column : date time derived from time-stamp
    df.index = pd.to_datetime(df.index, unit='s')
    #resample data
    r = df.resample(rule='60S')
    df = r.mean()
    return df
```

#Function name : vector_angle_global
#Author : Arshia Zernab Hassan
#Function description:
Calculate and add global vector angles to Data Frame to a dictionary

#Input Parameters:
1. Pandas Data Frame with headers –
   Frame  Time  X.1  Z.1

#Return:
1. Data frame with headers –
   Frame  Time  X.1  Z.1  vector  theta

#pre-condition:
   1. data frame has valid value

"""
def vector_angle_global(df):
    #create column of vector [X, Z] – 4th column
    #([X, Z] is a vector from origin to data point L(X, Z))
    temp_vector = list()
    for row in range(0, len(df)):
        temp_vector.append(np.array([float(df.iloc[row, 2]), float(df.iloc[row, 3])]))
    df['vector'] = temp_vector  # add column under 'vector' heading

    #calculate angle between vectors and add to list
    temp_theta = list()
    for row in range(0, len(df)-1, 1):
        # cos(theta) = dot_product(u, v)/length(u)/length(v); u and v are vectors
        cos_theta = np.dot(df.iloc[row, 4], df.iloc[row+1, 4]) / np.linalg.norm(df.iloc[row, 4]) / np.linalg.norm(df.iloc[row+1, 4])
        #if cos(theta) is in valid range

if cos_theta <= 1.0 and cos_theta >= -1.0 :
    #theta = acos(.);
    theta = math.degrees(math.acos(cos_theta))
    #add value of theta
    temp_theta.append(theta)
else :
    #add nan
    temp_theta.append(np.nan)

#pad array to match length of dataframe
for pad in range(len(temp_theta), len(df)) :
    temp_theta.append(np.nan)

#add newly calculated angle list to dataframe under header 'theta' -
5th column
df['theta'] = temp_theta

return df

""
#Function name : vector_angle_relative
#Author : Arshia Zernab Hassan
#Function description :
Calculate and add relative vector angles to Data Frame
to a dictionary
#Input Parameters :
1. Pandas Data Frame with headers –
Frame  Time  X.1  Z.1
#Return :
1. Data frame with headers –
Frame  Time  X.1  Z.1  vector  theta
# pre-condition:

1. data frame has valid value

```python
def vector_angle_relative(df):
    # create column of vector [X₂−X₁, Z₂−Z₁] - 4th column
    # ([X₂−X₁, Z₂−Z₁] is a vector from data point L₁(X₁,Z₁) to L₂ (X₂,Z₂))
    temp_vector = list()
    for row in range(0, len(df)-1):
        x21 = df.iloc[row+1,2] - df.iloc[row,2]
        z21 = df.iloc[row+1,3] - df.iloc[row,3]
        temp_vector.append(np.array([x21, z21]))
    # pad array to match length of dataframe
    for pad in range(len(temp_vector), len(df)):
        temp_vector.append(np.nan)
    df['vector'] = temp_vector  # add column under 'vector' header

    # calculate angle between vectors and add to list
    temp_theta = list()
    for row in range(0, len(df)-2,1):
        # cos(theta) = dot_product(u,v)/length(u)/length(v); u and v are vectors
        cos_theta = np.dot(df.iloc[row,4], df.iloc[row+1,4]) / np.linalg.norm(df.iloc[row,4]) / np.linalg.norm(df.iloc[row+1,4])
        # if cos(theta) is in valid range
        if cos_theta <= 1.0 and cos_theta >= -1.0:
            # theta = acos(.)
            theta = math.degrees(math.acos(cos_theta))
            # add value of theta
            temp_theta.append(theta)
```

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else:
    #add nan
    temp_theta.append(np.nan)

    #pad array to match length of dataframe
    for pad in range(len(temp_theta), len(df)):
        temp_theta.append(np.nan)

    #add newly calculated angle list to dataframe under header 'theta' – 5th column
    df['theta'] = temp_theta

    return df

""
#Function name : rate_of_change_angle
#Author : Arshia Zernab Hassan
#Function description :
Calculate and add 'rate of change of angles' to Data Frame
#Input Parameters :
1. Pandas Data Frame with headers –
Frame Time X.1 Z.1 vector theta
#Return :
1. Data frame with headers –
Frame Time X.1 Z.1 vector theta rate
#pre-condition :
1. data frame has valid value

""
def rate_of_change_angle(df):
    #create column of vector angle change rate – 6th column
temp_rate = list()

for row in range(0, len(df) - 1):
    #dT = T2−T1
denom = (float(df.iloc[row+1,1])−float(df.iloc[row,1]))
    if denom != 0:
        #rate = (theta2−theta1)/dT
        angle_rate = (float(df.iloc[row+1,5])−float(df.iloc[row,5]))
        / denom
        #add value of rate
        temp_rate.append(angle_rate)
    else:
        #add nan
        temp_rate.append(np.nan)

#pad array to match length of dataframe
for pad in range(len(temp_rate), len(df)):
    temp_rate.append(np.nan)

#add newly calculated 'rate of angle change' list to dataframe under header 'rate' - 6th column
df['rate'] = temp_rate
df.dropna() #discard all rows with nan

return df

""
#Function name : calculate_distance
#Author : Arshia Zernab Hassan
#Function description :
Calculate and add 'distance between consecutive points' to Data Frame
#Input Parameters :
1. Pandas Data Frame with headers —

Frame | Time | X.1 | Z.1 | vector | theta | rate | distance

#Return : 1. Data frame with headers —

Frame | Time | X.1 | Z.1 | vector | theta | rate | distance

#pre-condition:

1. data frame has valid value

""

def calculate_distance(df):
    temp_distance = list() #
    for row in range(0, len(df)-1): #for all rows in data frame
        x21 = df.iloc[row+1,2] - df.iloc[row,2] #difference between x coordinates of the two points
        z21 = df.iloc[row+1,3] - df.iloc[row,3] #difference between z coordinates of the two points
        distance = math.sqrt(math.pow(x21,2) + math.pow(z21,2)) #segment length between two points
        temp_distance.append(distance) #add to list

    #pad array to match length of dataframe
    for pad in range(len(temp_distance), len(df)):
        temp_distance.append(np.nan)

    #add newly calculated 'segment length' list to dataframe under header 'distance' - 7th column
    df['distance'] = temp_distance

    return df

"""
#Function name : algo_1
#Author : Arshia Zernab Hassan
#Function description :
Count number of wandering traces in movement data
#Input Parameters :
1. Data frame with headers —
Frame  Time  X.1  Z.1  vector  theta  rate  distance
#Return :
Wandering trace count
#pre-condition :
1. data frame has valid value

```python
def algo_1(df):
    has_sharp = False  #variable to keep track of sharp point encounter
    segments = 0  #variable to keep track of segments between sharp points
    wandering = 0  #variable to keep track of wandering trace

    for row in range(0, len(df) - 1):  #for all rows in data frame
        if df.iloc[row, 5] >= 90:  #if angle is equal or more than 90 degrees (5th column) (a sharp point)
            if has_sharp==False:  #if this is the first sharp point
                row1=row  #save the current row as first sharp point row
                has_sharp = True  #a sharp point has been encountered
            else:  #if there is a previous sharp point
                row2=row  #save the current row as second sharp point row
                distance = df.iloc[row1:row2, 7].sum()  #sum of segment lengths between the last two sharp points
                if distance < 10:  #if segment length smaller than threshold
```
segments += 1  #add to segment count

if segments==4 :  #if segment count is equal or
    #more than 4
    wandering += 1  #add to wandering trace count

else :
    segments = 0  # re-initialize segment count to 0
    row1=row2  #set previous sharp point by current sharp
    point

return wandering  #return wandering trace counts

Listing A.3: algorithm to detect wandering trace (algo.py)
A.2 Code Flow Diagrams

Figure A.1: Wandering Trace Detection
Figure A.2: Vector Angle Calculation
Figure A.3: Vector Angle Calculation (Free vectors)
Figure A.4: Rate of Angle change calculation
df : dataframe with sequence of location coordinates X and Z

temp_distance = empty list;
row = 0

Calculate segment lengths between sharp points

row<length(df)

False

pad temp_theta with nan to match length of df;
df['DISTANCE'] =
temp_distance

df

True

x21 = df[row+1]['X'] - df[row+1]['X'];
z21 = df[row+1]['Z'] - df[row+1]['Z'];
distance = sqrt(pow(x21, 2) + pow(z21, 2));
temp_distance.append(distance);
row++

Figure A.5: Segment Length calculation