IDENTIFYING NURSING ACTIVITIES TO ESTIMATE THE RISK OF CROSS-CONTAMINATION

by

Kaveh Seyed Momen

A thesis submitted in conformity with the requirements for the degree of Doctor of Philosophy
Graduate Department of Institute of Biomaterials and Biomedical Engineering
University of Toronto

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Abstract

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Hospital Acquired Infections (HAI) are a global patient safety challenge, costly to treat, and affect hundreds of millions of patients annually worldwide. It has been shown that the majority of HAI are transferred to patients by caregivers’ hands and therefore, can be prevented by proper hand hygiene (HH). However, many factors including cognitive load, cause caregivers to forget to cleanse their hands. Hand hygiene compliance among caregivers remains low around the world.

In this thesis I showed that it is possible to build a wearable accelerometer-based HH reminder system to identify ongoing nursing activities with the patient, indicate the high-risk activities, and prompt the caregivers to clean their hands.

Eight subjects participated in this study, each wearing five wireless accelerometer sensors on the wrist, upper arms and the back. A pattern recognition approach was used to classify six nursing activities offline. Time-domain features that included mean, standard deviation, energy, and correlation among accelerometer axes were found to be suitable features. On average, 1-Nearest Neighbour classifier was able to classify the activities with 84% accuracy.

A novel algorithm was developed to adaptively segment the accelerometer signals to identify the start and stop time of each nursing activity. The overall accuracy of the algorithm for a total of 96 events performed by 8 subjects was approximately 87%. The accuracy was higher than 91% for 5 out of 8 subjects.
The sequence of nursing activities was modelled by an 18-state Markov Chain. The model was evaluated by recently published data. The simulation results showed that the high-risk of cross-contamination decreases exponentially by frequency of HH and this happens more rapidly up to 50%-60% hand hygiene rate. It was also found that if the caregiver enters the room with high-risk of transferring infection to the current patient, given the assumptions in this study, only 55% HH is capable of reducing the risk of infection transfer to the lowest level. This may help to prevent the next patient from acquiring infection, preventing an infection outbreak. The model is also capable of simulating the effects of the imperfect HH on the risk of cross-contamination.
Dedication

To my wife Maryam and my son Koorosh, my mom and dad, Gitty and Nasser for their unconditional love, support, and encouragement ...
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List of Abbreviations

1-NN  1-Nearest Neighbour

ANOVA  Analysis of Variance

AR  Autoregressive

ARFF  Attribute-Relation File Format

C. Difficile  Clostridium Difficile

CDAD  Clostridium Difficile-Associated Diarrhea

DT  Decision Trees

EMG  Electromyographic

FEMA  Failure Mode and Effects Analysis

HAI  Hospital Acquired Infections

HH  Hand hygiene

HID  Human Interface Device

ICU  Intensive Care Units

IV  Intravenous

MOHLTC  Ministry of Health and Long-Term Care
MRSA  Methicillin Resistant Staphylococcus Aureus

NB  Naïve Bayes

PS3  Sony PlayStation 3

RAM  Random Access Memory

RFID  Radio frequency identification

RLS  Recursive Least Squares

S. Aureus Staphylococcus Aureus

SMA  Signal Magnitude Area

SVM  Support Vector Machines

TA  Tilt Angle

TRI  Toronto Rehabilitation Institute

USB  Universal Serial Bus

VAG  Vibroarthrographic

VRE  Vancomycin-Resistant Enterococci

WHO  World Health Organization
Chapter 1

Introduction

1.1 Motivation

Hospital Acquired Infections (HAI) are an increasing patient safety concern affecting hundreds of millions people around the world [1, 2]. It is estimated that about 1.4 million patients have a HAI at any given time [3]. In North America HAI are believed to be responsible for 100,000 patients deaths each year [4, 5].

HAI are infections that patients acquire while being treated in the hospital for something else. HAI is a contributing factor in extending the hospital length of stay [4, 6]. In addition, bed closures, resulting from infectious outbreaks, can become a major disruption to timely admission and often lead to increased wait times. Therefore, HAI are a big economic burden on healthcare systems.

HAI are preventable to some degree. It is believed that better hand hygiene practise by caregivers is the single most effective intervention to reduce the rate of HAI [7, 8, 9, 10, 11]. However, poor hand hygiene compliance by caregivers has been reported in the past studies [12, 13, 14]. Many factors, including cognitive load, cause caregivers not to properly wash or cleanse their hands, contributing to low handwash compliance rates. A few studies implemented hand hygiene reminder techniques, including patient
involvement in hand hygiene programs [15], electronic voice prompts at the entrances to patient rooms on a nursing unit, the utility room, and the staff lavatory [16, 17], and electronically monitored areas around the patient along with instrumented soap and alcohol dispensers [18], to overcome the caregivers’ forgetfulness to cleanse hands.

Although all of these techniques have shown promising results, none of them is yet capable of reminding the caregivers to cleanse hands during caregiving procedures. Some of these procedures require cleansing after completion of tasks where there is a risk of contamination by contact with body fluids that are usually referred to as “dirty” activities. Others, require cleansing before performing tasks such as dressing wounds that are usually referred to as “clean” activities. Transitions from “dirty” to “clean” activities are considered high-risk because the contaminating agents can enter the patient’s system. Indeed, previous studies reported low hand hygiene compliance for such high-risk activities [19, 20, 21].

It seams that there is an opportunity to extend prompting technologies to address these before-aseptic and post-contaminating moments.

### 1.2 Objective

The objectives of the presented work in this thesis were:

1. To test the feasibility of an intelligent system that automatically recognizes examples of everyday bed-side nursing activities, including examples of aseptic procedures and body fluid exposure. This work would provide the basis for adding more intelligent hand hygiene prompts for Toronto Rehabilitation Institute (TRI) electronic hand hygiene reminder system, which currently only addresses the need to cleanse hands before touching the patient or the patient’s environment and after leaving the environment [18].

2. To develop a risk-based model that uses real-time nursing activity information to
help prompt the caregivers wash their hands when it is absolutely necessary (high-risk activities). This model might serve as an advancement to the current logic of TRI hand hygiene reminder system, which attempts to identify every opportunity for hand hygiene with the same urgency regardless of the level of risk presented.

1.3 Summary of the approach

I designed and prototyped a portable system that recorded and processed specific nursing activities using accelerometer sensors. These sensors were taken from the hardware of an inexpensive game controller to save cost. I took a pattern recognition approach to process raw acceleration data recorded from samples of nursing activities. In this approach, suitable features that represent nursing activities were extracted from the signal. This work was presented as a peer-reviewed conference paper in the 34th Canadian Medical And Biological Engineering Society conference. This work constitutes Chapter 3 of this thesis.

I continued the work on recognizing nursing activities from acceleration signals and I evaluated the feasibility of such method. My approach suggested that on average, six typical nursing activities namely, talking to a patient, checking on vital signs, replacing an Intravenous (IV) bag, checking on blood sugar, placing a bedpan under the patient, and giving oral medication to a surrogate patient could be recognized by such a system with 85% success rate, where the accuracy was averaged over eight subject nurses. This work was published in the peer-reviewed Technology and Healthcare journal, and constitutes Chapter 4 of this thesis. The section that describes the technology development overlaps with some parts of the presented conference paper.

Although my approach showed acceptable success rate in recognizing a few examples of nursing activities, a trained observer marked the start and stop time of each nursing activities during the data collection. This obviously limited the ability of such system to
be used in real-life practises, where the onset of each nursing activity should be automatically recognized by the system in real-time. To solve this issue I used adaptive filtering and segmentation techniques. I developed an algorithm that could automatically recognize the start and stop time of each nursing activity, recorded by accelerometer sensors. The overall accuracy of the algorithm for a total of 96 events performed by 8 subjects was about 87%. The accuracy was higher than 91% for 5 out of 8 subjects. The details of this work has been published also in Technology and Healthcare. This paper constitutes Chapter 5 of this thesis.

In order to meet the second objective of this research I used the principles of stochastic (random) processes to mathematically model the sequence of care activities that generally happen around a patient in a typical hospital room. I developed this model to estimate the risk of infection transfer accumulated by the caregiver at the time of leaving the patient, given the rate of complied hand hygiene opportunities. As the type of nursing activity is a contributing factor in the total risk of infection transfer by the caregivers’ hands, such a model might help to prompt the caregivers to wash their hands when it is absolutely necessary. This model would be combined with a nursing activity recognition system that was developed and discussed in Chapter 4, and an intelligent hand hygiene reminder system such as TRI’s hand hygiene reminder system. This work is presented in detail in Chapter 6 of this thesis and was submitted for publication to a scientific peer-reviewed Journal and it is under review.

1.4 Thesis overview

Chapter 2 presents a review of the literature relevant to the work that appears in this thesis. Chapters 3 and 4 describe the development of the novel wireless wearable technology to time-stamp and record acceleration data from nursing activities. These chapters also include the results of relevant pattern recognition approaches I used to recognize
nursing activities. In Chapter 5, I describe a novel algorithm that automatically marks the start and stop time of nursing activities that can also be used to mark the transition points of human activities recorded by accelerometers. To my knowledge, this approach was not previously used to segment the acceleration data recorded from human activities. In Chapter 6, I describe a novel mathematical model to estimate the risk of cross-contamination based on the World Health Organization (WHO) guidelines for hand hygiene. The WHO guidelines aim to help caregivers recognize the moments they need to wash their hands during patient care activities. I extended these guidelines by considering the risk of infection transfer associated with each hand hygiene moment. I developed this model to optimize the logic behind future versions on TRI’s intelligent hand hygiene reminder system. This model if combined with the nursing activity recognition system that I developed in this work, will have the potential to be used in an advanced hand hygiene reminder system that prompts the user to wash their hands based on the task and its associated risk. Such advanced technology could help increase compliance by relating the likely importance of satisfying a particular opportunity for hand hygiene to the relative risk of infection transfer and reflecting that risk in the urgency (e.g. amplitude of vibration or other characteristics) of the prompting signal. The current systems treat all opportunities as equal in importance which may be unrealistic for a busy nurse encountering about 350 hand hygiene opportunities per patient per day [22]. This model can also be used as an epidemiological model to predict an infection outbreak if supplied by appropriate data. This thesis ends with discussion, conclusions, and suggested future work presented in Chapter 7.

1.5 Summary of contributions

Figure 1.1 summarizes the contributions of this thesis. These contributions will be discussed more in detail in Section 7.1.
Chapter 1. Introduction

Contributions

Methods
Developed a risk-based model based on WHO HH guidelines. The model can identify high-risk moments. The model may be used to optimize the prompts in an intelligent HH reminder system.

Simulation suggests that 50%-60% HH seems to be adequate to keep the risk of infection transfer low.

Technology
Developed a low-cost, truly wireless accelerometer-based human activity recognition system.

Developed a method to identify nursing activities from accelerometer signals. Time-domain features and 1-NN classifier resulted in 84% accuracy.

Developed a method to automatically mark the onsets of nursing activities. Overall accuracy was 87%. 5 of 8 subjects had accuracy > 91%.

The algorithm may be able to mark the onsets of sub-components of nursing activities.

Developed a low-cost, truly wireless accelerometer-based human activity recognition system.

Figure 1.1: Summary of contributions
Chapter 2

Literature Review

2.1 Hospital Acquired Infections

Hospital Acquired Infections (HAI), Nosocomial infections, Healthcare-associated infections are synonyms for infections that patients acquire from the hospital environment during the course of receiving treatment for other conditions\(^1\). It is estimated that about 5% to 15% of people admitted to hospitals are affected by HAI [14]. These numbers are higher for patients admitted to Intensive Care Units (ICU) affecting 9% to 37% of ICU patients [14]. This is probably due to the use of various invasive devices such as central venous catheters, mechanical ventilations and urinary catheters [23]. On average, it is estimated that 1.4 million patients have HAI at any given time worldwide [3]. HAI significantly prolong hospital stays [4, 6] and can be devastating and even deadly.

The global economic burden of HAI and associated mortality rate are unknown. However data from the U.S. studies report that 90,000 deaths are associated with HAI annually in the U.S. and the financial burden of HAI on the U.S. healthcare system increased from 4.5 billion in 1992 to 6.5 billion in 2004 [23].

There are many types of HAI. Urinary tract infection (usually catheter-associated),

\(^1\)Patients can also acquire HAI from community or at home from a home nurse
Table 2.1: Summary of major HAI frequencies and associated severities. Aggregated data from [24, 25, 26]).

<table>
<thead>
<tr>
<th>Type of infection</th>
<th>Frequency</th>
<th>Length of stay</th>
<th>Mortality and cost</th>
</tr>
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<tbody>
<tr>
<td>Urinary tract</td>
<td>35%</td>
<td>1 to 4 days</td>
<td>Low</td>
</tr>
<tr>
<td>Surgical sites</td>
<td>20%</td>
<td>7 to 8.5 days</td>
<td>Medium</td>
</tr>
<tr>
<td>Bloodstream infection</td>
<td>15%</td>
<td>7 to 21</td>
<td>High</td>
</tr>
<tr>
<td>Pneumonia</td>
<td>15%</td>
<td>25.5±22.8 days</td>
<td>High</td>
</tr>
</tbody>
</table>

surgical-site infection, bloodstream infection (usually associated with the use of an intravascular device), and pneumonia (usually ventilator-associated) comprise the majority of HAI [24].

Catheter-associated urinary tract infections are the most frequent but they carry the lowest mortality and lowest cost [24]. Bloodstream infections and ventilator-associated pneumonia, which are less common but have a more severe impact than others in terms of mortality and extra costs, are rapidly increasing in frequency particularly in cases due to antibiotic-resistant organisms [14, 24]. Surgical-site infections are second in frequency and third in cost [24, 25]. Table 2.1 summarizes the HAI frequency and their associated costs and mortalities.

It has been shown that the hands of caregivers are contaminated by HAI pathogens during caregiving activities [14, 27, 28]. Therefore, caregivers’ hands are considered to be one of the most important vehicles to transfer infection among patients. Here I briefly describe important pathogens that have been widely reported to cause HAI.

### 2.2 HAI pathogens

HAI are caused by a wide variety of common and unusual bacteria, fungi, and viruses. Methicillin Resistant Staphylococcus Aureus (MRSA), Vancomycin-Resistant Enterococci (VRE), and Clostridium difficile (C. difficile) are very important HAI pathogens. All the materials discussed in this thesis are applicable only to HAI agents that are trans-
mitted by direct physical contact, particularly the pathogens that are transmitted by the hands of caregivers, thereby excluding air-borne HAI pathogens.

2.2.1 Methicillin Resistant Staphylococcus Aureus (MRSA)

Staphylococcus aureus (S. Aureus) is a Gram-positive bacterium that is carried asymptomatically on the skin surface of approximately 30% of the population at a given time [29]. S. aureus is mostly colonized in anterior nares. After the establishment of local infection, S. aureus may spread to the bloodstream and infect other sites, causing serious diseases including endocarditis\(^2\), central nervous system infection (e.g. meningitis), pneumonia, skin and soft tissue infection, surgical site infection, and urinary tract infection [30].

Factors that promote colonization include coincident respiratory infection, prolonged hospitalization, needle use (as in intravenous drug users), diabetics, patients with burns, patients requiring hemodialysis, patients receiving allergy shots, exposure to cold weather, dermatologic conditions such as eczema [30]. Antibiotic administration has also been reported as a colonization risk factor probably by alteration of normal flora that is known to provide resistance to S. Aureus colonization [31].

S. Aureus is highly sensitive to a family of antibiotics called \(\beta\)-Lactam antibiotics, including penicillin. During normal bacteria reproduction, a group of proteins called \textit{penicillin-binding proteins} (PBPs) facilitate the process of cell wall synthesis. \(\beta\)-Lactam antibiotics bind to PBPs and inhibit the cell wall construction, and cause the bacteria to shed their cell walls and fail to divide, forming large, fragile spheroplasts. Overtime bacteria often develop resistance to \(\beta\)-Lactam antibiotics by synthesizing an enzyme called \(\beta\)-Lactamase. This enzyme then attacks the \(\beta\)-Lactam structure in antibiotics.

MRSA by definition are strains of S. Aureus that have developed resistance to certain antibiotics including methicillin and have become a major cause of invasive disease among

\(^2\)An inflammation of the inner layer of the heart that usually involves the heart valves
hospitalized patients [29]. MRSA are deadly virulent pathogens in hospitals, long-term care facilities and the community [30].

MRSA is principally transmitted from patient to patient via the hands of healthcare workers rather than by the acquisition of resistance during antibiotic treatment via spontaneous mutation [32, 33]. MRSA can stay on inanimate surfaces from 4 weeks to 7 months [34]. It has been shown that MRSA on the hands of caregivers usually are transient and removed by proper hand washing [14].

### 2.2.2 Vancomycin-Resistant Enterococci (VRE)

Enterococci are Gram-positive bacteria that are normally found in most people’s gastrointestinal tract and they rarely cause illness in healthy people. Enterococci have been also found in hospitalized patients’ skin, wounds, and chronic bedsores [30, 35]. There are a total of 21 enterococci species and among those, *enterococcus faecalis* and *enterococcus faecium* are the major human pathogens, accounting for 60%-90% and 5% to 16% of clinical isolates of enterococci respectively. Most enterococci are inherently resistant to many antibiotics. In the past, a type of an antibiotic called Vancomycin was considered a reliable agent for enterococcal strains with resistance to other antibiotics agents. However, in 1986 a new strain of enterococci was reported in Europe that was resistant to Vancomycin. Since then, Vancomycin-Resistant Enterococcui (VRE) related infections have been increasingly reported in the U.S. and worldwide and several types of VRE have been studied and reported in the literature [30].

Healthy people are unlikely to get VRE and if they do become colonized with the bacteria, they rarely become ill. People at risk for colonization or infection with VRE are usually found in hospitals and have an underlying medical condition which makes them susceptible to infection. These conditions include critically ill patients in intensive care units, patients with severe underlying disease or problems with their immune system, patients who have had major surgery, patients with urinary catheters and renal failure,
and patients who have received many antibiotics, particularly Vancomycin [30].

Early studies suggested that enterococci isolated from sites of infection were from the hosts own gastrointestinal tract. However, numerous studies have shown that person-to-person spread of enterococci is a significant mode of transmission of nosocomial enterococci. It has also been reported that the environment may have a role in VRE spread. However it is not clear if the environment becomes colonized passively by patients fecal flora or actively by using medical equipment (e.g. electronic thermometers) on multiple patients [30].

Enterococci can cause urinary tract infection, blood stream infection, endocarditis, intraabdominal and pelvic infections, skin and soft tissue infections, neonatal sepsis and meningitis [30]. As antibiotic resistance in the enterococcus increases in prevalence and therapeutic options become more limited, the prevention of emergence and spread of resistant enterococci is very important.

2.2.3 Clostridium Difficile (C. Difficile)

Clostridium Difficile (C. Difficile) is a type of rod-shaped Gram-positive bacterium that causes severe diarrhea when competing bacteria in the gastrointestinal tract flora have been eliminated by antibiotics. Each case of C. Difficile-Associated Diarrhea (CDAD) costs $3,669 and results in 3.6 excess hospital days. A conservative annual cost estimate for CDAD in the United States is $1.1 billion [36]. In a Canadian study, the authors calculated that readmission for CDAD costs $128,200 (Canadian dollar) per hospital per year [37].

C. Difficile is present in the stool of 2% to 5% of the general population and at higher rates among hospitalized patients and infants [38]. C. Difficile is capable of forming endospores\(^3\). An endospore is a dormant, tough, and temporarily non-reproductive structure of the bacteria and its formation is usually triggered by a lack of nutrients.

\(^3\)In the literature the term spores is loosely used as equivalent to endospores [38].
During endospore formation, the bacterium divides within its cell walls. One side then engulfs the other side [38]. Endospores can survive without nutrients for a very long time. They are resistant to ultraviolet radiation, high temperature, extreme freezing and chemical disinfectants.

C. Difficile becomes pathogenic when at least three critical conditions are met [30]:

1. Disruption of the normal colonic microflora that is usually caused by antimicrobial therapy.

2. Exposure to toxigenic C. Difficile that occurs most often in hospitals and chronic-care facilities, which serve as the main reservoirs for this infection. When a patient is exposed to C. Difficile one of three outcomes may happen: the patient becomes colonized but remains asymptomatic, the patient develops CDAD, or potentially the patient does not develop any detectable infection. Once the patient is established as an asymptomatic carrier, data indicate that the patient is at decreased risk for subsequent CDAD.

3. The risks of illness include increased age, severe underlying illness, and length of hospital stay.

The source of CDAD in nonepidemic settings has not been determined [30]. However, the environment and the hands of caregivers have been considered as possible sources of infection. The literature suggest that cohorting, patient isolation, hand washing, glove use, environmental cleaning and disinfection, and antimicrobial restriction are effective in preventing and controlling CDAD [30].

2.3 Microbial Flora of Hands

Philip Price [39] in 1938 studied the bacteria on skin and he divided them into two groups namely: resident flora, and transient flora.
Resident flora is a group of different bacteria that normally reside on the surface of the skin. The population density of resident skin flora on the hands remains constant for a long period of time for each individual and only diseases of the skin and antibiotics agents or disinfectants may cause long-term alterations [30]. The normal skin flora is believed to prevent colonization of other microorganisms [30] by converting the skin lipids into free fatty acids that are well-known for their antifungal and bactericidal properties [40], by secreting antibiotic-like agents, and by competing for nutritions [14]. The resident skin flora is not considered pathogenic unless it is introduced into body tissue by trauma or in the presence of foreign objects such as catheters or implants. Resident flora are difficult to remove by mechanical means [30, 14].

Transient flora are a group of bacteria that are usually abundantly present on exposed skin. In the hospital environment caregivers usually acquire these type of flora by direct contact with the patients and patient’s immediate environment. Transient flora contaminate the skin, do not normally multiply on dry skin, and do not survive for a very long time. However, high pathogenic agents can be found among transient skin flora. Certain types of transient flora can sporadically multiply on the skin surfaces [14] and slowly become resident flora [39]. Unlike resident flora, transient bacteria are loosely attached to the surface of the skin and can be easily released from the hands [30]. Therefore, transient flora are ideal agents to transfer from the caregivers’ hands to the patients especially when the hands and surfaces are wet [41]. Therefore, in order to prevent the spread of transient flora, proper hand hygiene is crucial.

2.4 Hand hygiene

Many studies have shown that caregivers contaminate their hands during patient care [14, 22, 41]. The pathogens are spread by the hands of caregivers if the following five conditions are met [7]:

1. Organisms must be present on the patient's skin or have been shed onto inanimate objects immediately surrounding the patient.

2. Organisms must be transferred to the hands of caregivers.

3. Organisms must be capable of surviving for at least several minutes on caregivers' hands.

4. Handwashing or hand antisepsis by the caregivers must be inadequate or omitted entirely, or inappropriate agents must be used for hand hygiene.

5. The contaminated hand(s) of the caregiver must come into direct contact with another patient or with an inanimate object that will come into direct contact with the patient.

If hands are known to be or are suspected of being contaminated, the transient pathogen must be removed from the hands to make them safe for the next patient [30]. Indeed, several studies have shown that proper hand hygiene is considered the most important measure in preventing HAI [7, 11, 42, 9, 43, 14].

Based on the recent World Health Organization (WHO) guidelines on hand hygiene [14]:

- Hands must be washed with soap and water when visibly dirty or soiled with blood or other body fluids or after using the toilet.

- If exposure to potential spore-forming pathogens is strongly suspected or proven (e.g. outbreaks of C. Difficile) hand washing with soap and water is the preferred method.

- Use alcohol-based handrubs as the preferred method for routine hand cleansing in all other caregiving activities.
When hands are washed with soap and water the hands must first be wet with water and apply the necessary amount of product to cover all surfaces, including under the fingernails. Then, hands must be rinsed with clean, and running water, and dried thoroughly with a single-use towel. Finally, a towel must be used to turn off tap/faucet [14].

When alcohol-based hand-rubs are used to cleanse hands, a palmful of the product must be applied to the hands to cover all surfaces, including under the fingernails. Hands must be rubbed together until they are dry.

It should be noted that in order to make hand washing effective, fingernails must be kept short, and it is recommended that artificial nails, jewelry, and rings not be worn [14].

2.4.1 The WHO “My five moments for hand hygiene” model

In order to standardize hand hygiene training, observation, and performance reporting among health-care setting around the globe, WHO proposed a model for hand hygiene called “My five moments for hand hygiene” [44]. In this model the caregiving area around the patient is divided by two virtual zones, patient zone and health care zone.

The patient zone includes the patient and all the immediate surroundings. The patient zone includes the intact skin of the patient, all inanimate surfaces that are touched by or in direct physical contact with the patient such as the bed rails, bedside table, bed linen, infusion tubing and other medical equipment. It further contains surfaces frequently touched by caregivers during care activities such as monitors, knobs and buttons, and any other “high frequency” touched surfaces [14]. The model is also valid for patients sitting in a chair or being received by physiotherapists in a common treatment location [14].

Any space outside the patient zone is considered the health care zone. Based on this model all caregivers must cleanse their hands as soon they enter the patient’s zone, following “five moments”, namely:

1. Before touching a patient (Moment1)
2. Before a clean/aseptic procedure (Moment2);

3. After body fluid exposure risk (Moment3),

4. After touching a patient (Moment4)

5. After touching patient surroundings (Moment5).

Moment1 hand hygiene is to prevent colonization of the patient with HAI pathogens, resulting from the transfer of pathogens from the environment to the patient through unclean hands. For example Moment1 prevents spreading the pathogens after touching the door handle. While the caregiver is in the patient zone, he or she is likely to touch objects or the intact skin of the patients within the patient zone. This transfers pathogens from the patient zone to the hands of the caregiver. Moment2 of hand hygiene model is designed to prevent transferring pathogens from the caregivers to a critical site with infectious risk for the patient, such as opening a venous access line, giving an injection, or performing wound care. The purpose of Moment3 of hand hygiene model is to prevent transmission of pathogens from the hands of the caregivers to the patient zone surfaces. This also reduces the risk of a transmission of microorganisms from a “colonized” to a “clean” body site within the same patient and more importantly it reduces the risk of colonization or infection of caregivers with pathogens that may occur even without visible soiling [7]. Moment4 and Moment5 are to prevent the spread of the pathogens from the patient zone to the health care zone. This also reduces contamination of caregivers’ hands with the pathogens from the patient they just visited, protects the caregivers themselves, an other patients [14].

Coincidence of two moments for hand hygiene

Two moments for hand hygiene may sometimes fall together. Typically, this happens when moving directly from one patient to another without touching any surface outside the corresponding patient zones (Moments 4 and 1 coincide). Another example of such
a simultaneous moment would be the direct access to a clean activity as a first hand-to-
surface exposure after entering the patient zone (moments 1 and 2 coincide). Therefore
in these situation, a single hand hygiene action will cover the two moments for hand
hygiene [14].

Two patients within the same patient zone

It may happen that two or more patients are in such close contact that they occupy the
same physical space and touch each other frequently. For example, a mother stays in the
her patient zone with her newborn child, or two patients sharing a single bed or beddingspace. In these cases, it is conceptually difficult to recognize the actual compliance with
the five moments. Therefore, the WHO model suggests viewing the two close patients as
occupying a single patient zone. Hand hygiene is certainly still required when entering
or leaving the common patient zone and before and after critical sites according to their
specific nature, but the indication for hand hygiene when shifting intact skin contact
between the two patients is probably of little preventive value because they are likely to
share the same microbial flora [14].

2.4.2 Hand hygiene compliance

While proper hand hygiene has been shown to be the single most effective intervention
that fights HAI [7, 11, 42, 9, 43, 14], previous studies have shown that compliance with
hand hygiene among caregivers is relatively low [14, 13, 45]. Previous research identified
several factors that include [14] lack of knowledge of guidelines for hand hygiene, lack of
recognition of hand hygiene opportunities during patient care, and lack of awareness of
the risk of cross-transmission of pathogens, lack of time, lack of appropriate infrastruc-
ture and equipment in the healthcare facility, skin irritation and dermatitis after using
handwashing agents, and lack of a role model from colleagues or superiors.

The WHO responded to this issue by launching the “Clean Care is Safer Care” pro-
gram as part of the “First Global Patient Safety Challenge” in 2005 [2, 1]. The WHO guidelines also propose strategies for successful promotion of hand hygiene in health-care settings, including: [14]

- System change (e.g. make hand hygiene possible, easy and convenient).
- Hand hygiene education.
- Promote/facilitate skincare for caregivers’ hands.
- Routine observation and feedback.
- Improve institutional safety climate (e.g. avoid understaffing, institute administration sanction/reward).
- Reminders in workplace.

Although implementing such individual strategies has shown success in increasing hand hygiene compliance rates it is only a temporary change. This is most likely because the dynamic of behavioural change is complex and multifaceted [46]. For example, the lack of knowledge of infection control measures has been repeatedly shown after training [46]. Larson et. al. [45] reported that wide dissemination of hand hygiene guidelines alone was not sufficient motivation for a change in hand hygiene behaviour. Haas and Larson [47] reported that making alcohol handrubs more conveniently available by introducing portable handrub dispensers did not significantly improve hand hygiene compliance rate and it was not sustainable either. The authors concluded that the increased availability of hand hygiene products was only a single intervention within a broad multimodal approach. Thus, it seems that the combination of education, motivation, and system change including performance feedback and reminders, are crucial to improve sustainable hand hygiene compliance rate [46].
2.4.3 Hand hygiene reminders

In addition to education, motivation and system change, reminders play an important role in sustaining the improvement of hand hygiene compliance. McGuckin et. al. showed that hand wash compliance rate was increased when patients were asked to provide reminders to their caregivers to prompt hand washing [15]. Although this prompting method worked for patients willing to participate in the study, it is not clear how this technique works for patients who have not been trained, or are incapable or reluctant to ask the staff if they have cleansed their hands. Swoboda et. al. [16, 17] demonstrated that an automated electronic voice prompting system installed at the entrances to patient rooms on a nursing unit, the utility room, and the staff lavatory resulted in improved hand hygiene compliance and HAI rates. Yet, no sustainability was tested.

Researchers at Toronto Rehabilitation Institute (TRI), in Canada have designed a novel system that detects when a caregiver enters or leaves monitored zones around patient beds [18]. The system records any hand hygiene actions performed with either wearable alcohol gel dispensers, stationary alcohol gel dispensers, or soap dispensers. Assuming the patient/patient’s environment contact happens upon entering the zones, the system uses location and hand hygiene activity information to decide on whether hand hygiene is necessary and prompts the user accordingly. Moreover, the system is capable of recording and reporting the hand hygiene compliance for “before” and “after” patient contact.

Although all these techniques have shown promising results, none of them is yet capable of reminding the caregivers to cleanse hands during the caregiving procedures. These procedures are usually referred to “clean” and “dirty” procedures. These procedures correspond to Moment2 (Before a clean/aseptic procedure) and Moment3 (body fluid exposure risk) of WHO “five moments for hand hygiene” model that was presented in Section 2.4. Indeed, previous studies reported low hand hygiene compliance with Moment2 and Moment3 [19, 20, 21]. Therefore, it seems that there is a need to improve hand
hygiene reminder technologies and include a feature to identify care activities between dirty and clean sites on the patients and issue a reminder accordingly.

Another issue that has attracted more attention in the literature is that full compliance with hand hygiene may not be feasible [20] since it requires up to 230 minutes per day per patient in certain settings [22]. Therefore, if an intelligent hand hygiene reminder system is used in such settings the caregivers will receive a high number of prompts to perform hand hygiene. A high incidence of seemingly irrelevant reminding prompts may lead to important prompts being ignored [48].
Chapter 3

Suitable Features for Accelerometer-based Nursing Activity Recognition System

The contents of this chapter was presented as a scientific peer-reviewed conference paper:

K. Momen and G. Fernie, Suitable features for accelerometer-based nursing activity recognition system. In the proceedings of the 34th Canadian Medical And Biological Engineering Society, Toronto, Canada, held on June, 5-8, 2011.

Contribution of authors: K. Momen wrote the manuscript, developed the technology, research design and protocol, and collected and analyzed the data. G. R. Fernie, reviewed the manuscript, and led the research project.

In this chapter, I briefly explain how accelerometer sensors used in an inexpensive game controller can be attached to the wrists, upper arms and back of caregivers to record acceleration data from nursing activities. My aim in this study was to use pattern recognition approach to identify examples of nursing activities by classifying the patterns of the corresponding acceleration signals. Once a system is able to identify nursing activities, it may be possible to differentiate “dirty” from “clean” nursing activities and
prompt the caregiver to perform a proper hand hygiene if it is missed.

The first step in pattern recognition approach\(^1\) is to extract meaningful features representing the caregivers’ activities. Thus, I extracted two popular feature sets from the accelerometer signals that are used in human activity recognition systems. I compared their performances in classification of six examples of nursing activities. In Chapter 4, I extracted the recommended features learnt from the current work and I analyzed the patterns of accelerometer signals recorded from nursing activities in greater detail. Therefore, the technology development and data collection section overlaps partly with Chapter 4.

3.1 Introduction

Approximately 1 of 10 patients admitted to North American hospitals pick up infections from the hospital environment while being treated for something else. Hospital Acquired Infections (HAI) are believed to be responsible for up to 88,000 deaths in the U.S. [4] and 8000 death in Canada [5]. HAIs cost 4.5 billion to the North American health care system annually [4, 6]. Several studies have shown that HAIs can be prevented if hospital staff practise optimal hand hygiene [8, 9, 7].

At Toronto Rehabilitation Institute in Canada we are developing technologies to promote optimal handwashing. We have developed a handwash reminder system that reminds caregivers to wash their hands before and after visiting a patient [49]. We are working on enhancing this system to help remind caregivers to wash their hands between nursing procedures, as required by the guidelines.

To achieve this, we are investigating the possibility of using wearable accelerometers to identify relevant nursing activities. Accelerometers have been used to identify simple human activities such as walking, running, and sitting [50, 51, 52, 53, 54].

In the literature human activities are usually classified using pattern recognition ap-
proaches, such as Decision Tables, Decision Trees (DT), Naïve Bayes (NB), and 1-Nearest Neighbour (1-NN) [50, 51, 53, 55, 56, 57, 58]. In this approach the original signal is approximated by suitable features over a sliding window. The extracted features form a multi-dimensional feature space. Some of the data points are used to train supervised classifiers. The rest of the data are used to validate and test the classifiers’ performances.

Previous researchers mostly used the signal statistics of accelerometers as their preferred feature sets, including mean, standard deviation, energy, and correlation between accelerometer axes [50, 51, 53, 54, 59]. Recognition accuracy of up to 80% was reported in classifying simple human activities including sitting, standing, walking, and running.

Later, Khan et. al. [60, 61] used a novel feature set that included autoregressive (AR) model coefficients [62], Signal Magnitude Area (SMA) [52, 63], and Tilt Angle (TA) of accelerometer signals. They obtained impressive 99% accuracy in recognizing lying, standing, walking and running activities.

Although the above methods have shown success in their respective research areas it is not clear how these successful feature extraction methods perform in identifying nursing activities, where the activities are more complex than sitting, standing, walking and running in nature.

The objective of this work is to evaluate and compare the performance of the above two feature extraction methods in identifying simple nursing activities using accelerometers.

3.2 Method

3.2.1 Data collection

We used 5 Sony PlayStation®3 (PS3) DUALSHOCK®3 SIXAXIS™ game controllers to record acceleration data from 8 subject nurses wirelessly. The subjects wore the controllers on their left and right wrists, left and right upper arms, and their backs.
Each PS3 controller included a KXPC4 3-axis accelerometer (Kionix Inc., Ithaca, New York, the U.S.A.) and a XV3500 1-axis gyroscope (Epson-Toyocom Corporation, Tokyo, Japan). As these controllers were designed to capture hand accelerations while the user was playing an intensive game, we expected these controllers would be suitable in recording accelerations from nursing activities.

Figure 3.1 illustrates the PS3 hardware, housed in a custom box that was designed and manufactured in our in-house rapid-prototyping facility. Figure 3.2 illustrates a nurse wearing 5 PS3 controllers while replacing an IV bag.

We established a wireless link between the PS3 controllers and a laptop computer (Intel Celeron 1.6GHz, 1.5 GB RAM) running Ubuntu Linux 8.04 (Hardy) operating system (Kernel 2.6.24-24), based on the protocol provided by the publicly available instructions [65]. We developed a software program (C programming language) to receive raw acceleration packets from each PS3 controller, and save them to a simple text file. The program time-stamped the arrival of each data packet with 1 microsecond accuracy. The PS3 sampling frequency was estimated to be 44.41 Hz.

We used an additional unmodified PS3 controller (the 6th controller) to label and time-stamp the nursing activities; we assigned start, stop, and nursing task events to separate buttons on the controller. This controller was connected to the same computer as the other PS3 controllers wirelessly.
Chapter 3 - Suitable Features for Nursing Activity Recognition

The subjects performed 10 trials of each of the following nursing activities in sequence: 1) talking to a patient, 2) checking on vital signs, 3) replacing an intravenous (IV) bag, 4) checking on blood sugar, 5) placing a bedpan under the patient, and 6) giving oral medication to a surrogate patient. We wrote a program in MATLAB® (The MathWorks Inc. Natick, the U.S.A.) to automatically segment the complete data to the corresponding nursing activity intervals based on the start and stop time of each nursing activity recorded by the 6th controller. In total, 300 data segments (10 trials * 6 activities * 5 sensors) were saved in MATLAB® standard data file for each subject.

3.2.2 Data analysis

We extracted the features on 256-sample windows of acceleration data (N=256) on each axis with 50% overlapping between consecutive windows and created two separate feature spaces. One of the feature spaces included the mean, standard deviation, energy, and correlation between accelerometer axes calculated for each accelerometer axis. From now on we refer to this feature space as time-domain feature space.

The mean of the acceleration signal calculated over the feature extractor window is the DC component of the signal. The standard deviation of the acceleration signal is useful in capturing the range of possible acceleration values to separate activities that may look similar in nature but different in their speed and acceleration (e.g. walking vs. running). The energy of the signal is a measurement of the signal strength and it is useful to capture the intensity of an activity and can be obtained either in the time or frequency domain. The correlation among accelerometer axes is useful in distinguishing activities that may appear similar but are performed in different dimensions.

We referred to the second feature space as the augmented AR coefficients feature space including third-order AR coefficients, SMA, and TA as disclosed by Khan et. al. [60, 61]. The AR model of the current sample of the signal $x(n)$ is described as a linear combination of previous samples plus an error term $e(n)$ which is independent of past samples and is
calculated by [62]:

\[ x(n) = \sum_{k=1}^{p} a_k x(n - k) + e(n), \quad (3.1) \]

where \( x(n) \) is the current sample of the modelled signal, \( a_k \) are the AR coefficients, \( p \) is the model order, and \( e(n) \) is the prediction error. SMA is the signal magnitude calculated over all axes and it has been shown to be useful in identifying static vs. dynamic activities [52, 60, 61]. SMA is calculated by:

\[ SMA = \sum_{n=1}^{N} (|x(n)| + |y(n)| + |z(n)|), \quad (3.2) \]

where \( x(n) \), \( y(n) \), \( z(n) \) are the acceleration samples for each axis at time \( n \), and \( N \) is the number of samples in the feature extraction window. TA is the tilt angle from the gravity vector and is calculated by:

\[ TA = \arccos(\bar{z}), \quad (3.3) \]

where \( \bar{z} \) is the mean of the \( z \) axis signal calculated over the feature extraction window and it is parallel to the gravity vector.

We wrote a program in MATLAB® to extract the features and converted them into Attribute-Relation File Format (ARFF) recognizable by the Weka machine learning tool [66]. Weka is a very powerful open source data mining tool developed by the University of Waikato - New Zealand, and has been used in human activity data mining research [50, 51]. We used the Weka Experimenter tool to analyze and compared the performance of 1-NN classifier on the two different feature spaces. The 1-NN algorithm is a method in pattern recognition for classifying data points based on the distance between a data point and the training sets in the feature space [66].
Table 3.1: Comparison of overall sensors’ accuracies, evaluated by 1-NN classifier, averaged over all activities for all subjects.

<table>
<thead>
<tr>
<th>Sensor Location</th>
<th>Average 1-NN Classifier Accuracy(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Time-domain features</td>
</tr>
<tr>
<td>Left Wrist</td>
<td>84.88±3.81</td>
</tr>
<tr>
<td>Right Wrist</td>
<td>85.42±5.44</td>
</tr>
<tr>
<td>Left Upper Arm</td>
<td>81.42±5.78</td>
</tr>
<tr>
<td>Right Upper Arm</td>
<td>82.51±5.43</td>
</tr>
<tr>
<td>Back</td>
<td>84.76±3.75</td>
</tr>
<tr>
<td>Average</td>
<td>83.80±4.92</td>
</tr>
</tbody>
</table>

3.3 Results

Table 3.1 illustrates the sensors’ average accuracies computed by 1-NN classifier based on 10-fold cross-validation test on both feature spaces. In the k-fold cross-validation method the data is randomly divided into k segments. Each segment is used as a test set and the remaining k-1 segments serve as the training set. Later, this procedure is repeated k times and then the average result is reported. In this research we chose k=10 which is a common practise in machine learning applications [66]. It can be seen that the time-domain features outperformed the augmented AR model coefficients features on average by 20%.

3.4 Conclusion

We compared the performance of two separate feature sets that had previously shown success in recognizing simple human activities such as lying, sitting, standing, walking, and running. Although the augmented AR model coefficient features had shown superior performance in recognizing simple human activities [60, 61], on average they showed 20% less accuracy performance than the time-domain features in recognizing nursing activities. On average the 1-NN classifier was able to identify 6 different nursing activities with
83.80%±4.92% accuracy using the time-domain feature set.
Chapter 4

Nursing Activity Recognition Using an Inexpensive Game Controller: An Application to Infection Control

The material presented in this chapter was published as a journal article:


The contents of this chapter are identical to the publication except for a footnote added to Section 4.4.1 to clarify that the accelerometer sensors sampling rates were indeed constant. This footnote was added based on my examining committee request at the time of my final thesis defence. The formatting of this chapter was also done according to University of Toronto requirements.

Contribution of authors: K. Momen wrote the manuscript, developed the technology, research design and protocol, and collected and analyzed the data. G. R. Fernie, reviewed the manuscript, and led the research project.

No permission was required from the publisher to reproduce the article as the pub-
In this chapter I explain the instrumentation setup used to record acceleration data from six examples of nursing activities as well as the data collection protocol. The accelerometer sensors that were taken from inexpensive game controllers were attached to the wrists, upper arms and backs of eight caregivers participated in the study. In this work I used the recommended feature set that was evaluated in Chapter 3 and I compared the performance of three popular classifiers on the extracted feature sets. The classifiers were evaluated on two different data sets recorded in different sessions. The results of the study suggests that it is possible to identify few examples of nursing activities using accelerometers attached to the back of caregivers with acceptable recognition accuracy.

This chapter ends with an amendment section that was not part of the original published paper. This amendment was later added based on the request of my departmental examining committee to amplify the performance of the chosen classifier in this study.

4.1 Abstract

It is estimated that 10\% of the patients admitted to North American hospitals die of hospital acquired infections. Approximately half of these are thought to be a consequence of poor hand hygiene practises by the hospital staff. Electronic hand washing reminders that prompt caregivers to wash their hands before and after the patient/patient’s environment contact may help to increase the hand hygiene compliance rate. However, the current systems fail to identify the nursing procedures happening around the patient to issue proper hand hygiene prompt.
In this research we used the hardware of a low-cost wireless Sony game controller, which included a 3-axis accelerometer, to identify six nursing activities happening around a patient. We attached five sensors to eight nurses’ left and right wrists, left and right upper arms, and the backs. Each nurse performed 10 trials of each nursing activity in sequence, followed by a combined nursing activities trial.

We extracted mean, standard deviation, energy, and correlation among axes per sensor and compared the results of 1-Nearest Neighbour (1-NN), Decision Tree (J48), and Naïve Bayes classifiers. 1-NN classifier had the best performance and on average regardless of the sensor locations, we achieved 84% ±2% accuracy.

4.2 Introduction

Hospital acquired infections (HAI) are one of the most important patient safety problems. It is estimated that over 1.4 million people worldwide are infected with HAI [2]. In the USA, HAI are responsible for 88,000 deaths annually and cost 4.5 billion to the health care system [4]. In Canada, it is estimated that approximately 8,000 patients die from HAI annually [5]. Canadian hospitals spend up to $100 million per year treating patients with infections contracted in the hospital [6]. HAI are a contributing factor in extending the hospital length of stay [67, 68]. In addition, bed closures, resulting from infectious outbreaks, can become a major disruption to timely admission and often lead to increased wait times.

Several studies [8, 9, 7] have shown that hand washing is the most important single intervention for preventing HAI. However, poor compliance with hand washing protocols by hospital personnel has been reported in these studies. The World Health Organization (WHO) responded by launching the “Clean Care is Safer Care” program as part of the First Global Patient Safety Challenge in 2005 [2, 1], The WHO proposed new guidelines on hand hygiene training, observation, and performance reporting in health
care settings [44, 69]. These guidelines were adapted by the Ontario Ministry of Health and Long-Term Care (MOHLTC) in Canada [70]. According to the Ontario MOHLTC new guidelines caregivers need to cleanse their hands in “4 moments”. These moments, usually referred to “hand wash opportunities”, are [70]:

- Before initial contact with the patient or the patient environment (M1 moment)
- Before performing any aseptic procedure (M2 moment)
- After any body fluid exposure risk (M3 moment)
- After patient or patient environment contact (M4 moment)

Several interventions have been suggested to increase the hand washing compliance rate, including, patient engagement, and ongoing monitoring and hand wash observations [70]. McGuckin et. al. showed that hand wash compliance rate is increased if patients are asked to provide reminders to their caregivers to prompt hand washing [15]. Although this prompting method works, the improvement is difficult to sustain and the technique does not work for patients who have not been trained, or are incapable or reluctant to ask the staff if they have cleansed their hands. Swoboda et. al. [16, 17] demonstrated that an automated electronic voice prompting system installed at the entrances to patient rooms on a nursing unit, the utility room, and the staff lavatory resulted in improved hand hygiene compliance and HAI rates. However, the system does not address hand hygiene compliance for patient contact, aseptic procedures or body fluid risk, nor does it address issues of long term sustainability that may result from over prompting.

Researchers at Toronto Rehabilitation Institute (TRI), in Canada have designed a novel system that detects when a caregiver enters or leaves monitored zones around patient beds [49]. The system records any hand hygiene actions performed with either a wearable, stationary alcohol gel, or soap dispensers. Assuming the patient/patient’s
environment contact happens upon entering the zones, the system uses location and hand hygiene activity information to decide on whether hand hygiene is necessary and prompts the user when necessary. Currently, this system does not record any information about activities happening within the zones. This may result in unnecessary prompts for activities that do not require patient/patient’s environment contact (e.g. talking to the patient with hands in pocket). Such seemingly irrelevant reminding prompts may lead to important prompts being ignored. Moreover, this system does not recognize any procedures that require hand cleansing within the patient’s zone (i.e. aseptic procedures, body fluid exposure) to issue a proper hand hygiene prompt.

In this research we aim to enhance TRI’s system by using technology to identify the nursing activities within the patient’s zone. Once the nursing activities are identified, we will be able to estimate hygiene opportunities based on the recommended hand hygiene rules (i.e. the Ontario MOHLTC rules, WHO rules). This information may be integrated into future versions of TRI’s intelligent hand wash reminder system.

4.3 Background

There are two main types of human activity recognition systems; vision-based systems and accelerometer-based wearable systems. Although vision-based systems that use surveillance cameras to monitor human activities have shown success [71, 72] this approach may not seem attractive in healthcare settings where the cost of installation and the privacy of the patients are primary concerns. Wearable sensors may be an appealing alternative. These sensors, which usually include accelerometers and gyroscopes, are low-cost, small in size, and unlike vision-based systems, the wearer has more freedom to move outside of the monitored area.

Many researchers have studied human activities by attaching accelerometers to their subjects. These studies used single accelerometer [52, 73, 51], multiple accelerometers [50,
74, 75], and hybrid sensors [76, 77, 78, 53] to study simple repetitive activities such as walking, running, and sitting. These activities are usually classified using pattern recognition approaches, including Decision Tables, Decision Trees (DT), Naïve Bayes (NB), 1-Nearest Neighbour (1-NN) [50, 74, 51], Support Vector Machines (SVM) [75, 51], and Hidden Markov Models [76, 73].

To our best knowledge, only one group has investigated the possibility of using accelerometers to detect routine nursing activities. Ohmura et. al [75] developed a wireless accelerometer sensor called “B-Pack”, which was not bigger than a match box in size. The study used four B-Packs on a subject’s chest, waist, left and right upper arms to identify seven different nursing activities including walking, checking on vital signs, transferring a patient to a wheelchair, bed bath, nurse call, and an intravenous (IV) injection. They extracted mean, standard deviation, energy, and correlation of each axis per device and combined all features to create a 48-feature vector. They obtained an impressive 96.8% accuracy using 1-NN classification method based on a 10-fold cross-validation of the data but did not report how many subjects and trials per subject were performed. The authors noted that more experiments were needed to confirm the accuracy of their system.

Later, Naya et. al. [74] added location information to their experiment with “B-Pack” sensors to increase the accuracy of their classification. Three nurses participated in their study and each nurse performed two trials. They studied nursing activities and used an analysis method similar to their previous work [75]. They evaluated the performance of the classifiers on two different datasets. Dataset1 used data recorded from both trials, mixed together and cross validated. Dataset2 used one of the trials’ data as the training and the other trial as the test. Unlike their previous report, their highest calculated accuracy for dataset1 was 81.6% ± 4.7% for 1-NN classifier and the accuracy on the dataset2 was the highest for SVM classifier (54.1% ± 12.8%). Unfortunately, the authors did not report why the accuracy on the most recent study was considerably lower.
especially for dataset\textsuperscript{2}. Moreover, it seems that in both of these studies the extracted features from individual sensors were combined together offline. Thus, the reported accuracy results are valid as long as the nurse carries all four sensors at the same.

In today’s modern hospitals caregivers are already loaded with different tools and equipment. Bulky or numerous wearable activity detection sensors would likely interfere with nurses’ routine work and therefore, it is desirable to use minimum number of small and lightweight sensors on the caregivers’ bodies. For practical implementation in a hospital, a low-cost discrete system that minimizes changes in infrastructure is more attractive. Therefore, the individual sensors should be intelligent enough to identify nursing activities in real-time and issue a hand hygiene reminder if necessary.

Our preliminary objective in this research was to determine if individual wearable accelerometer-based sensors could identify few simple nursing activities. We were also interested in identifying the most suitable and reliable location on a caregiver’s body where the sensors can be attached and at the same time least interfere with caregivers’ activities.

4.4 Method

4.4.1 Instrumentation

At the time of designing this research we realized that the majority of commercially available accelerometer-based wearable sensors were not suitable; Some of these sensors, although advertised as wireless sensors, needed individual sensors to be connected to a wireless module using wires, potentially interfering with caregivers’ routine work. Therefore, we investigated the possibility of using a low-cost accelerometer-based video game controller in our research.

We used a Sony PlayStation\textsuperscript{\textcopyright} 3 (PS3) DUALSHOCK\textsuperscript{\textcopyright}3 SIXAXIS\textsuperscript{TM} game controller, which includes a KXPC4 3-axis accelerometer (Kionix Inc., Ithaca, New York, the U.S.A.)
and a XV3500 1-axis gyroscope (Epson-Toyocom Corporation, Tokyo, Japan). The PS3 controller includes a Bluetooth module as well as a USB connector. The PS3 controller operates as a Human Interface Device (known as HID) both in USB and Bluetooth mode [65].

The KXPC4 accelerometer is capable of measuring linear acceleration from 1.5 g to 6 g (g is the gravity acceleration vector that is about 9.8 m/s² in SI units). This value is factory programmed and not user selectable. However, as these PS3 controllers are well designed to capture maximum hand accelerations while the user is playing intensive games we expected that they would perform well for nursing activities. Figure 4.1 illustrates the motherboard of the PS3 controller indicating the location of the gyroscope sensor and the accelerometer (the joysticks are removed) as well as the custom case that was designed and manufactured in our in-house rapid-prototyping facility.

Figure 4.1: The PS3 hardware housed in the custom case. The accelerometer (KXPC4) and the gyroscope (XV-3500) locations along with their axes relative to the case are shown. The two thin wires connect pin 8 and 9 of J3 connector on the motherboard to a miniature pushbutton (not shown) on the back of the case. This pushbutton replaces ‘PS’ button on the original PS3 case, and needs to be pushed to activate the controller.

We established a wireless link between the PS3 controllers and a laptop computer (Intel Celeron 1.6GHz, 1.5 GB RAM) running Ubuntu Linux 8.04 (hardy) operating system (Kernel 2.6.24-24), based on the protocol provided by the publicly available instructions [65]. It is possible to connect up to seven wireless PS3 controllers to a computer and simultaneously record raw acceleration data by enforcing the link mode as “Master”
in the Ubuntu Bluetooth configuration file. We used a Kensington (Redwood Shores, the U.S.A.) Bluetooth USB Adapter 2.0 on the Linux machine.

The PS3 controllers send raw acceleration and raw gyroscope data, as well as the status information about the buttons as 64-byte packets [65]. We developed a software program (C programming language) to receive raw acceleration packets from each PS3 controller and save them to a simple text file. The program time stamped the arrival of each data packet with 1 microsecond accuracy. We converted the raw acceleration data into the corresponding SI units based on the gravity vector g value (9.8 m/s²).

The sampling rate was estimated to be 44.41±0.51 Hz and it was calculated by inverting the averaged arrival time difference between two consecutive samples. On average, the maximum sampling interval variability among all five PS3 controllers used in this study did not exceed 0.3 ms¹, which is well below the suggested maximum negligible delay of 10ms in monitoring human activities [50, 75, 79].

### 4.4.2 Protocol

The protocol was approved by the TRI (Canada) Research Ethics Board. Participants were recruited from the nurses and nursing students who responded to our recruitment poster posted at two of the TRI sites. A total of 8 nurses (Subject3-Subject7), and nursing students (Subject1, Subject2 and Subject8) participated in our study. All the participants gave informed written consent. All nurses and nursing students were eligible to participate provided that they could speak and understand English, not be pregnant, and not have any medical conditions that might become worse by performing the required physical tasks such as a mobility impairment or a cardio respiratory problem.

Each participant wore five PS3 sensors on the left and right wrists, left and right upper

¹The actual sampling rate of the device was constant. However, since at the time of this publication the sampling rate was not disclosed by the PS3 designers, we needed to estimate it over the wireless link. The small variation in the calculated sampling rate was due to the inevitable delay in the Bluetooth frequency hopping. Bluetooth systems avoid interference from other signals by hopping to a new frequency after transmitting or receiving a packet.
arms and on the upper mid back between the scapulae (Table 4.1). The sensor boxes were fastened to the participant’s body parts using elastic straps. Originally a manikin was used as a patient to whom the nurses provided care. Based on the feedback we received from the early participants, starting with Subject5 we replaced the manikin with a real person so that the nurses could simulate the caregiving activities more naturally. The surrogate patient volunteer, who remained the same for the rest of the entire project, gave the informed consent to participate in the study.

We used an additional unmodified PS3 controller (the 6th controller) to label and time stamp the start and stop of each nursing activity per trial. This additional controller was wirelessly connected to the same computer as the other controllers. Therefore, the absolute arrival time and time stamps for all the data packets were the same for all six connected controllers. We created a program (C programming language) to decode, time stamp, and save the buttons status data, received from the 6th PS3 controller. The complete instrumentation setup is illustrated in Figure 4.2.

The participants were asked to perform the following nursing activities in sequence:

1. Talking to the patient.

2. Checking on blood pressure. An automated blood pressure monitor was used as the standard practise in our hospital. No stethoscope was used to listen to the heart beats.

3. Replacing an IV bag. This was simulated without the needle puncture.

4. Checking on the blood sugar. This was simulated with a fake Accu-Check® device. No real blood samples were taken from the patient.

5. Placing a bed pan.

6. Giving oral medication. This was simulated; medicine was not given to the patient.
Table 4.1: The sensors designation

<table>
<thead>
<tr>
<th>Sensor No.</th>
<th>Location attached</th>
<th>Orientation of the box</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Left wrist</td>
<td>x-axis pointed towards left fingers</td>
</tr>
<tr>
<td>2</td>
<td>Right wrist</td>
<td>x-axis pointed towards right fingers</td>
</tr>
<tr>
<td>3</td>
<td>Left upper arm</td>
<td>x-axis pointed towards left elbow</td>
</tr>
<tr>
<td>4</td>
<td>Right upper arm</td>
<td>x-axis pointed towards right elbow</td>
</tr>
<tr>
<td>5</td>
<td>Back</td>
<td>x-axis pointed towards feet</td>
</tr>
</tbody>
</table>

The subjects finished 10 trials of each nursing activity before performing the next activity. We chose the above six simple nursing activities as the most representative activities frequently occurring in our hospital research ward. The sequence of these nursing activities generates the subset moments of required hand hygiene opportunities according to the Ontario MOHLTC “4 moments for hand wash” rules. The participants were encouraged to perform the nursing activities at their own pace. However, for the activity “talking to the patient” they were asked to talk for more than 10 seconds so that our algorithm could capture enough samples to extract the corresponding features. A trained observer instructed the participant to start and stop the trials and marked the events using the dedicated 6th PS3 controller. A video camera was used to capture the complete scenario for later reference.

Upon completion of the 10th trial of the last nursing activity (‘Giving oral medi-
(recognition’), the subject was asked to perform an additional continuous complete scenario without any interruption; this trial, starting with greeting the patient, and ending with giving an oral medication to the patient, was recorded to capture any variations that may exist while performing combined nursing activities. This trial, referred to as the 11th trial, later served as one of the test trials for our algorithm. While recording the 11th trial, the trained observer did not instruct the nurse to start/stop any trial. The nurse performed the scenario, moving from one activity to another at her/his own pace, while the trained observer quietly time stamped the beginning and ending of each trial. Each data collection session lasted about 70 minutes. Figure 4.3 illustrates an example of acceleration data recorded by the all sensors on Subject5, while performing the 11th trial.

![Graph showing acceleration data](image)

Figure 4.3: An example of acceleration data recorded by all sensors on Subject5. This subject used body language while talking to the patient. The hatched areas were eliminated in data analysis.

Each body-worn PS3 controller continuously transmitted the acceleration data for
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the whole session and the corresponding file in ASCII format was created in the laptop computer. A program written in MATLAB\textsuperscript{\textregistered} (The MathWorks Inc. Natick, the U.S.A.) used the PS3 controllers data and the corresponding start/stop times to automatically segment the complete data to the specific nursing activities intervals. In total, 330 segmented data (11 trials * 6 activities * 5 sensors) was saved in MATLAB\textsuperscript{\textregistered} standard data file for each subject. An additional MATLAB\textsuperscript{\textregistered} program converted the segmented data into Attribute-Relation File Format (ARFF) recognizable by Weka machine learning tool [66]. Weka is a very powerful open source data mining tool developed by the University of Waikato- New Zealand, and has been widely used in human activity data mining research [50, 80, 74, 75, 51].

4.4.3 Data Analysis

We used pattern recognition approach to identify nursing activities from the raw acceleration data. In this approach, relevant features are extracted from a sliding window of limited samples of the signal. If \(m\) features are extracted from the signal, \(m\)-dimensional data points will be constructed in the feature space. Then, a subset of the data points in the feature space is used to train a classifier, and later other subsets of the recorded data points are used to validate the classifier’s performance.

We extracted mean, standard deviation, energy, and correlation among accelerometer axes features from the raw acceleration signal. These features have been extensively used in previous research and have been shown to be useful in recognizing human activities such as walking, standing, going up stairs, running, cycling, etc. [50, 76, 74, 73, 75, 51]. We did not use the gyroscope data in this study.

The mean of the acceleration signal calculated over the feature extractor window is the DC component of the signal. In a static situation, where there is no movement involved, this component indicates the amount of tilt of each accelerometer axis with respect to the gravity vector and can be directly used to estimate the posture and the orientation.
of each limb. However, in dynamic situations, this component indicates the average acceleration (including the gravity vector) sensed at each axis of the accelerometer. The mean of the discrete acceleration signal is calculated by:

$$\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i,$$  \hspace{1cm} (4.1)

where $x_i$ is the $i^{th}$ sample of the signal, and $n$ is the length of the extractor window.

In previous research, for activities that appear similar in nature but have different acceleration values, such as walking and running, the standard deviation of the signal was used to capture the range of possible acceleration values. The standard deviation of a discrete signal is calculated by:

$$\sigma = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x})^2},$$  \hspace{1cm} (4.2)

where $x_i$ is the $i^{th}$ sample of the signal and $\bar{x}$ is the signal mean calculated over the feature extractor window, and $n$ is the length of the window.

The energy of the signal is a measurement of the signal strength and it is useful to capture the intensity of an activity. The energy of the signal can be calculated either in time or in frequency domain [81]. We calculated the energy of the signal in time domain by:

$$E = \sum_{i=1}^{n} |x_i|^2,$$  \hspace{1cm} (4.3)

where $x_i$ is the $i^{th}$ sample of the signal, and $n$ is the length of the extractor window.

Past research studies have used the correlation among accelerometer axes to distinguish activities that may appear similar but are performed in different dimensions. For example, walking on a level surface involves the translation of the origin of the accelerometer coordinate system in one dimension whereas climbing stairs involves translation in
more than one dimension. The correlation is calculated by:

$$\text{Corr}_{x,y} = \frac{\text{Cov}(x,y)}{\sigma_x \sigma_y}$$

(4.4)

where $\text{Cov}(x,y)$ is the covariance between each pair of axes calculated over the feature extractor window, and $\sigma_x$ and $\sigma_y$ are the standard deviations of each axis.

We used Equations 4.1 to 4.4, to extract the features on 256-sample windows of acceleration data ($n=256$) on each axis with 50% overlapping between consecutive windows to create a 12-feature vector:

$$\vec{V}_j = [x_j, y_j, z_j, \sigma_x^j, \sigma_y^j, \sigma_z^j, E_x^j, E_y^j, E_z^j, \text{Corr}_{x,x}^j, \text{Corr}_{x,y}^j, \text{Corr}_{y,z}^j], \ 1 \leq j \leq \frac{N}{128}$$

(4.5)

where $N$ is the total number of samples between start and stop time of each activity in each trial (signal length), $j$ corresponds to the $j^{th}$ feature extractor window, and $x, y, z$ refer to the accelerometer axis on which the corresponding feature is calculated.

The 256-sample window length corresponds to 5.76 seconds with the sampling rate of 44.41 Hz. We chose these parameters to ensure the window length was long enough to cover full cycles of activities [50, 74, 51].

We used and compared the results obtained by 1-NN, NB, and DT (J48) classifiers on feature vectors $\vec{V}_i$ using Weka machine learning software.

In DT classification method the data pattern is modelled as a top down tree with branches and leaves. Each branch represents a feature on which the data will be split into subsets, and each leaf represents the classification results. DT classifiers work based on “divide-and-conquer” approach; looking for a feature to split on at each branch that best separates the classes. During the training process (known assigned classes for each data point), the DT algorithm uses maximum information gain (entropy) of each feature to use the most important and distinct feature to split the data into subsets. The algorithm
stops when the data can not be split any further. There are several versions that attempt to improve DT classifiers’ performances. We used version J48, which was implemented in Weka machine learning tool [66].

A Naïve Bayes classifier uses all features and allows them to make equal and independent contributions to the classification results. A Naïve Bayes classifier is based on Bayes’s rule of conditional probability and it “naïvely” assumes independence among the features. Therefore, the conditional probability $P$ for predicted class $C$ given features $F_1, F_2, \cdots, F_m$, is calculated by [66]:

$$
P(C|F_1, F_2, \cdots, F_m) = \frac{P(F_1|C) \times P(F_2|C) \times \cdots \times P(F_m|C) \times P(C)}{P(F_1, F_2, \cdots, F_m)}, \quad (4.6)$$

where in the numerator $P(F_m|C)$ is the $m^{th}$ feature probability distribution given class $C$, $P(C)$ is the prior probability of class $C$, and $m$ is the total number of features in the feature vector, which is set to 12 in this study. The denominator in Equation 4.6 is the features probability distribution, which is a constant and is later eliminated in the normalization process.

The k-nearest neighbours (k-NN) algorithm is a method in pattern recognition for classifying data points based on the distance between a data point and the training sets in the feature space. The training data points are stored in the memory with their corresponding class labels. In order to classify new data point, its distance to the k neighbouring data points are calculated and the decision is made based on the majority vote on the k neighbours class labels. When k=1, the algorithm simply assigns the new data point to the class of its nearest neighbour (1-NN).

### 4.5 Results

Data analysis was performed on two different datasets for each subject:

- Dataset1 consisted of 10 trials of the six different nursing activities as described in
Table 4.2: Comparison of overall sensors recognition rates, evaluated on Dataset1, averaged over all activities for all subjects. Accuracies above 80% are indicated in bold.

<table>
<thead>
<tr>
<th>Sensor Location</th>
<th>Average Classifier Accuracy(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NB</td>
</tr>
<tr>
<td>Left Wrist</td>
<td>79.83±5.78</td>
</tr>
<tr>
<td>Right Wrist</td>
<td><strong>81.93±6.57</strong></td>
</tr>
<tr>
<td>Left Upper Arm</td>
<td>76.96±5.97</td>
</tr>
<tr>
<td>Right Upper Arm</td>
<td>77.49±5.90</td>
</tr>
<tr>
<td>Back</td>
<td>78.95±7.32</td>
</tr>
</tbody>
</table>

the protocol. This dataset was used for cross-validation analysis.

• Dataset2 used Dataset1 as the training set, and used the 11<sup>th</sup> trial as the test set. (Referring to the protocol, for each subject the 11<sup>th</sup> trial was a continuous non-interrupted combined nursing activities started with “Talking to the patient” and ending with “Giving the oral medication to the patient”.)

The average accuracy results for NB, DT (J48) and 1-NN classifiers based on 10-fold cross-validation test on Dataset1 are summarized in Table 4.2. In the k-fold cross-validation method the data is randomly divided into k segments. Each segment is used as a test set and the remaining k-1 segments serve as the training set. Later, this procedure is repeated k times and then the average result is reported. In this research we chose k=10 which is a common practise in machine learning applications [66].

A corrected resampled t-test [66] confirmed that the accuracy of 1-NN was significantly higher than NB and DT (J48) classifiers evaluated on Dataset1 at 0.05 significance level. Thus, herein we focus on the results obtained by 1-NN classifier.

The overall recognition rates per subject for all sensors, averaged over the nursing activities evaluated on Dataset1 and Dataset2 are illustrated in Figure 4.4 and Figure 4.5 respectively. Table 4.3 reports the aggregate confusion matrix for the Back sensor (Sensor5), based on 10-fold cross-validation analysis on Dataset1, averaged over all subjects.
Similar confusion matrices were calculated for the other sensors and the summary of the results is reported in Table 4.4. A confusion matrix is a 2-dimensional matrix with actual classes usually in the rows and the predicted classes usually in the columns. Therefore, the diagonal elements show the number of correct class predictions and the off-diagonal elements indicate the number of misclassifications [66].

**Average accuracy among subjects on Dataset1**

![Average accuracy among subjects on Dataset1](image)

Figure 4.4: The average accuracy calculated by 1-NN classifier.

### 4.6 Discussion

Each complete nursing activity consists of smaller procedures or sub-activities. For example, placing a bedpan under the patient (assuming the bed pan is already on the bed, near the patient), requires the nurse to remove the patient’s blanket, roll the patient to the opposite side of the bed. While keeping the patient in this position with one hand, the nurse needs to place the bed pan under the patient with the other hand, roll back the
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Figure 4.5: The average accuracy calculated by 1-NN classifier.

For simplicity, in this research we did not breakdown each nursing activity of interest into smaller sub-activities. We considered each activity as a whole, which is the assumption behind our data analysis.

On average, using Dataset1, the 1-NN classifier classified six major nursing activities with more than 80% accuracy as demonstrated by Table 4.2. Figure 4.4 breaks down these results per subjects and shows how individual subjects performances contributed on the average performance. However, these results were based on Dataset1, which consisted of 10 annotated repeated trials of each nursing activity. Although we did not restrain the speed and the way the nurses performed the nursing activities, repetition of the task may have helped the subjects to perform the tasks in a certain way during the trials. Consequently, the PS3 sensors captured these repetitive nursing activities with acceptable accuracy.
Table 4.3: The Back sensor recognition rate; aggregated confusion matrix for 1-NN classifier tested on Dataset1, based on 10-fold cross-validation for 8 subjects.

<table>
<thead>
<tr>
<th>Predicted Activity</th>
<th>Actual Activity</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>a 424 6 27 2 12 22</td>
<td>a = Blood Sugar Test</td>
<td>86.00</td>
</tr>
<tr>
<td>b 6 366 11 0 1 14</td>
<td>b = Place a Bed Pan</td>
<td>91.96</td>
</tr>
<tr>
<td>c 14 9 259 1 14 16</td>
<td>c = Give Oral Medication</td>
<td>82.75</td>
</tr>
<tr>
<td>d 4 0 4 400 14 30</td>
<td>d = Replace an IV Bag</td>
<td>88.50</td>
</tr>
<tr>
<td>e 13 0 10 7 369 23</td>
<td>e = Talk to the Patient</td>
<td>87.44</td>
</tr>
<tr>
<td>f 18 21 22 22 22 302</td>
<td>f = Check on Blood Pressure</td>
<td>74.20</td>
</tr>
</tbody>
</table>

In contrast to the results illustrated in Figure 4.4, Figure 4.5 shows that the nursing activity recognition rate dropped when the algorithm was tested on Dataset2. This dataset used Dataset1 as the training, and used a fresh annotated continuous nursing activity dataset (the 11th trial) as the test data. This set was recorded approximately 1 hour later than the initial data collection. The results from this analysis suggested that the subjects may have performed the nursing activities differently, while combining the nursing activities together in the 11th trial; reviewing the recorded video clips confirmed the speed and the way the subjects did the activities varied for some subjects. For example, the speed that Subject1 and Subject4 performed the last continuous trial was not consistent with their speed during the first 10 repeated trials. Subject3 started singing and little dancing moves while providing continuous care to the manikin in the last trial. These additional body movements were not visible in the training set, resulting in the drop in the performance.

Interestingly, the inconsistency is more visible for the subjects who provided care to the manikin patient. Subject1 and Subject4 placed the bedpan under the manikin faster than their normal pace. They express that “lighter weight of the manikin” and its “lack of ability to express pain and discomfort” contributed in the subject’s faster performances. As described earlier, to prevent these problems happening to the rest
Table 4.4: Summary of the sensors recognition rates; each column of the table is obtained based on aggregated confusion matrix for 1-NN classifier tested on Dataset1, based on 10-fold cross-validation for 8 subjects.

<table>
<thead>
<tr>
<th>Activity</th>
<th>Sensors recognition rates (%)</th>
<th>Left wrist</th>
<th>Right wrist</th>
<th>Left upper arm</th>
<th>Right upper arm</th>
<th>Back</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blood Sugar Test</td>
<td></td>
<td>87.88</td>
<td>86.03</td>
<td>85.74</td>
<td>84.66</td>
<td>86.00</td>
</tr>
<tr>
<td>Bed Pan</td>
<td></td>
<td>85.50</td>
<td>82.89</td>
<td>84.96</td>
<td>81.53</td>
<td>91.96</td>
</tr>
<tr>
<td>Giving Oral Medication</td>
<td></td>
<td>82.74</td>
<td>80.89</td>
<td>79.61</td>
<td>76.83</td>
<td>82.75</td>
</tr>
<tr>
<td>Replace an IV Bag</td>
<td></td>
<td>90.87</td>
<td>93.12</td>
<td>84.36</td>
<td>90.56</td>
<td>88.50</td>
</tr>
<tr>
<td>Talking to the Patient</td>
<td></td>
<td>90.09</td>
<td>88.97</td>
<td>89.18</td>
<td>86.25</td>
<td>87.44</td>
</tr>
<tr>
<td>Check on Blood Pressure</td>
<td></td>
<td>76.24</td>
<td>76.20</td>
<td>66.00</td>
<td>71.15</td>
<td>74.20</td>
</tr>
</tbody>
</table>

of the data collection, starting with Subject5, we recruited a real person to act as the patient. Comparing the subject performances results in Figure 4.5 suggests that a real person acting as a patient helped the nurses to be more careful and consistent while performing the requested nursing activities.

The results for a one-way ANOVA test on Table 4.4 reveal that, on average, there is no significant difference between the mean of accuracy recognition rates among the sensors ($p$ value = 0.74857). These results suggest that in order to identify the six nursing activities evaluated in this research, and regardless of the location of the sensors, on average we expect to identify the nursing activities with 83.77% accuracy. However, some sensors have better performances to identify specific nursing activities, and depending on the application, any of the evaluated locations can be chosen.

Referring to the Back sensor confusion matrix in Table 4.3, it can be seen that on average 'bed pan' activity was recognized by this sensor with the highest accuracy (91.96%). These results are consistent with our expectations as the sensor attached to the back of the subject monitors the subjects’ postures; the subjects needed to bend towards the
patient while rolling the patient to the opposite side of the bed to place the bed pan. However, the Back sensor performance was lower when recognizing 'checking the vital signs' activity (74.20%). Referring to the last row of Table 4.3, it can be seen that the Back sensor almost equally confuses 'check on the blood pressure' activity with the rest of the activities, due to similarities among acceleration patterns sensed at the subject’s backs.

Based on the MOHLTC “4 moments for hand hygiene”, assuming that the nurse has already made contact with the patient (M1 occurred) and has not left the patient environment (M4 has not occurred yet), bedpan activity falls into the M3 handwash moment category and hand disinfection must happen after performing this activity. Thus, a sensor that can identify this activity with highest accuracy is preferable. Table 4.4 shows that the Back sensor has the highest recognition rate for bedpan activity (91.96%). The Back sensor also has a good recognition rate for blood sugar test (86%), which is a M2 handwash moment. Among all the six studied activities, the Back sensor has the lowest recognition rate for checking on blood pressure (74.20%), which includes only M1 and M4 handwash moments. This could be compensated with the help of the current TRI hand hygiene monitoring system, which already identifies M1 and M4 [49] (assuming the patient/patient environment contact happens as soon as the caregiver enters the zone). Thus, considering the high recognition accuracy for bedpan activity (M3) and blood sugar test (M2) it is desirable to place the sensor on the back of the subject.

Although all participants in this study were right-handed, reviewing the recorded video clips revealed that a few subjects were not consistent in using their dominant hand to perform some of the activities. For example, while a few subjects used their right hands first to remove the blanket in the bedpan activity, the same subjects used their left hands (or sometimes both hands) first to remove the blanket in some of the trials. It seems that placing a sensor on the back may address this problem as this location is less susceptible to the hand movement variations in performing certain nursing activities.
Placing the sensor on the back of the nurse may also interfere less with nursing activities and would be more preferable location in the infection control context; sensors worn on the back may require less disinfection in comparison to sensors worn on the wrists and other locations, where they may become contaminated more easily during caregiving activities.

A sensor worn on the back may also benefit from location information transmitted by infrared-based location sensors on the ceiling in such systems [49]. The location information has been shown to increase the nursing activity recognition rate [74].

Body language and extra random movements during some stationary activities such as 'talking to a patient' contributed to misclassification of these types of activities. As human beings, we perceive removing a bedpan or a blanket with left hand, right hand, or both hands as the same activity. Similarly, if somebody is talking to us with or without body language, we perceive both activities as 'talking'. These random movements while performing certain tasks are inevitable and cause misclassification problems for machine learning algorithms whose decisions are made based on crisp boundaries among classes. Classifiers that allow softer decision boundaries among classes such as fuzzy logic classifiers may help to increase the activity recognition rate accuracy. A recent study by Helmi and AlModarresi [80] demonstrated how a Fuzzy Interface System may increase the accelerometer-based activity recognition rate. Further tests are required to confirm the benefit of using fuzzy approach in detecting nursing activities.

### 4.7 Limitations

In this research we considered only six common nursing activities as they are performed at TRI complex continuing care site. More nursing activities should be considered to validate the reliability of the system in a broader context. Nevertheless, the results may not be generalized to the other healthcare settings as other centres may perform standard
nursing activities differently.

In each trial, the nursing activity data was extracted from the sensor acceleration data according to the start and stop time of each activity recorded by an observer. The data analysis was also performed offline. For practical implementation of an activity-based hand hygiene reminder system, it would be necessary to automatically detect the onsets of random nursing activities, extract them from a continuous stream of data, and classify the nursing activities in real-time. We are currently working on an algorithm that may help to identify the onset of the activities in real-time using singular spectrum-based change-point analysis [82].

Depending on the type of the nursing activities, the sub-activities are variable even with the same subjects [74]. Therefore, the speed of nursing activities and the order of the sub-activities vary depending on the situation (e.g. emergency care). A fixed-length feature extractor window may be too long or too short to properly extract features to capture these activities. This would result in poor classification performance. We are currently investigating if Dynamic Time Warping algorithm, which is a popular technique among speech recognition researchers, can help to address this problem.

This system currently discovers nursing activities after they are performed. Although it may increase hand hygiene compliance to remind caregivers after bed pan activity (example of M3) to cleanse their hands, it is not useful to detect the hand hygiene opportunity in blood sugar test (example of M2) after it occurs. A successful hand hygiene monitoring system needs to predict these events beforehand and issue a reminder for hand hygiene in advance. We are currently working on a stochastic Markov Chain model, which may be able to predict the occurrence of certain nursing activities, given the history of the performed nursing activities.
4.8 Conclusion and Future Work

In this research we showed how the hardware used in the Sony PlayStation® 3 game controller can be used in biomechanics studies, both for recording raw acceleration data and manual time stamping. These sensors are low-cost and are widely available. Up to 7 controllers can be connected to a Linux based operating system wirelessly. We used these sensors to identify six different simple nursing activities.

The results showed that on average regardless of sensor location, up to $83.80\% \pm 1.88\%$ accuracy can be obtained if 1-NN classifier is used. However, we showed that the sensor on the back of a caregiver is preferable to use. For the Back sensor, the accuracy was highest for 'bed pan' activity (91.96%) and the lowest for 'checking on vital signs' (74.2%). These results may help us to design an activity-based hand hygiene reminder and monitoring system based on any available standardized hand hygiene rules (i.e. the Ontario MOHLTC '4 moments of handwash')

We plan to perform more experiments with wider categories of nursing activities and investigate the possibility of using stochastic processes to predict the moments (M1 and M2), when hand hygiene needs to be perform in advance.

4.9 Amendment

Following the publication, the materials presented in this section have been added to amplify the performance of the 1-NN classifier.

Referring to Section 4.5 on average, 1-NN classifier achieved higher activity recognition accuracy and its performance was validated by a corrected resampled t-test at 0.05 significance level. Table 4.3 shows the performance of the 1-NN classifier broken down on the activities for the Back sensor.

In order to further study activity-based recognition performances of NB and DT(J48) classifiers and compare them to 1-NN classifier, respective aggregated confusion matri-
Table 4.5: The Back sensor recognition rate; aggregated confusion matrix for NB classifier tested on Dataset1, based on 10-fold cross-validation for 8 subjects.

<table>
<thead>
<tr>
<th>Predicted Activity</th>
<th>Actual Activity</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>a b c d e f</td>
<td>a = Blood Sugar Test</td>
<td>82.76</td>
</tr>
<tr>
<td>408 8 31 2 6 38</td>
<td>b = Place a Bed Pan</td>
<td>88.44</td>
</tr>
<tr>
<td>6 352 19 0 0 21</td>
<td>c = Give Oral Medication</td>
<td>77.64</td>
</tr>
<tr>
<td>24 15 243 2 9 20</td>
<td>d = Replace an IV Bag</td>
<td>87.61</td>
</tr>
<tr>
<td>5 0 3 396 13 35</td>
<td>e = Talk to the Patient</td>
<td>86.97</td>
</tr>
<tr>
<td>12 0 10 15 367 18</td>
<td>f = Check on Blood Pressure</td>
<td>57.49</td>
</tr>
<tr>
<td>37 34 23 33 46 234</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4.6: The Back sensor recognition rate; aggregated confusion matrix for J48 classifier tested on Dataset1, based on 10-fold cross-validation for 8 subjects.

<table>
<thead>
<tr>
<th>Predicted Activity</th>
<th>Actual Activity</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>a b c d e f</td>
<td>a = Blood Sugar Test</td>
<td>83.57</td>
</tr>
<tr>
<td>412 11 25 0 19 26</td>
<td>b = Place a Bed Pan</td>
<td>83.17</td>
</tr>
<tr>
<td>8 331 21 0 1 37</td>
<td>c = Give Oral Medication</td>
<td>76.36</td>
</tr>
<tr>
<td>31 13 239 4 11 15</td>
<td>d = Replace an IV Bag</td>
<td>88.05</td>
</tr>
<tr>
<td>4 2 3 398 16 29</td>
<td>e = Talk to the Patient</td>
<td>81.28</td>
</tr>
<tr>
<td>20 2 6 10 343 41</td>
<td>f = Check on Blood Pressure</td>
<td>65.11</td>
</tr>
<tr>
<td>24 31 22 32 33 265</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

ceses were calculated. Table 4.5 and Table 4.6 show examples of such confusion matrices computed for the Back sensor. Similar confusion matrices for all other sensors were computed and the summary of the results are reported in Table 4.7 and Table 4.8 for NB and DT (J48) classifiers respectively. Comparing these results to Table 4.4 suggests that on average 1-NN classifier has better activity recognition accuracy of 5% or more comparing to NB and DT (J48) classifiers. The confusion matrices for all sensors computed by 1-NN, NB, and DT (J48) classifiers are summarized in Appendix E, Appendix F, and Appendix G.
Table 4.7: Summary of the sensors recognition rates; each column of the table is obtained based on aggregated confusion matrix for NB classifier tested on Dataset1, based on 10-fold cross-validation for 8 subjects.

<table>
<thead>
<tr>
<th>Activity</th>
<th>Sensors recognition rates (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Left wrist</td>
</tr>
<tr>
<td>Blood Sugar Test</td>
<td>88.48</td>
</tr>
<tr>
<td>Bed Pan</td>
<td>83.00</td>
</tr>
<tr>
<td>Giving Oral Medication</td>
<td>79.15</td>
</tr>
<tr>
<td>Replace an IV Bag</td>
<td>83.91</td>
</tr>
<tr>
<td>Talking to the Patient</td>
<td>74.06</td>
</tr>
<tr>
<td>Check on Blood Pressure</td>
<td>69.80</td>
</tr>
</tbody>
</table>

Table 4.8: Summary of the sensors recognition rates; each column of the table is obtained based on aggregated confusion matrix for DT (J48) classifier tested on Dataset1, based on 10-fold cross-validation for 8 subjects.

<table>
<thead>
<tr>
<th>Activity</th>
<th>Sensors recognition rates (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Left wrist</td>
</tr>
<tr>
<td>Blood Sugar Test</td>
<td>83.64</td>
</tr>
<tr>
<td>Bed Pan</td>
<td>75.50</td>
</tr>
<tr>
<td>Giving Oral Medication</td>
<td>77.20</td>
</tr>
<tr>
<td>Replace an IV Bag</td>
<td>83.70</td>
</tr>
<tr>
<td>Talking to the Patient</td>
<td>83.73</td>
</tr>
<tr>
<td>Check on Blood Pressure</td>
<td>70.30</td>
</tr>
</tbody>
</table>
Chapter 5

Automatic detection of the onset of nursing activities using accelerometers and adaptive segmentation

The material presented in this chapter was published as an journal article:


The contents of this chapter are identical to the publication except for the formatting, which was done according to University of Toronto requirements.

Contribution of authors: K. Momen wrote the manuscript, developed the algorithm, and analyzed the data. G. R. Fernie, reviewed the manuscript, and led the research project.

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One of the challenges that most designers face in training intelligent devices is that a human observer needs to manually segment the data related to start and stop time of the signal produces by the device or the object in question. The system I developed in Chapter 4 works with acceptable accuracy as long as a trained observer marks the start and stop time of each nursing activity. However, this is not feasible in practise; an activity-based hand hygiene reminder system must be able to first detect the onset of the activity automatically, and then identify the activity itself. In this chapter I explain a novel algorithm that I developed to automatically mark the onsets of start and stop times of six examples of nursing activities discussed in Chapter 4.

5.1 Abstract

We used the Recursive Least Squares algorithm and a predictor filter to automatically identify the start and stop times of 6 simple nursing activities. The dataset included continuous acceleration recordings obtained with a single accelerometer sensor attached to the backs of 8 nurses.

The algorithm requires no training. It identifies the start and stop time of each activity when at least 2 of 3 axes show significant acceleration changes not more than a second apart. The overall accuracy of the algorithm for a total of 96 start and stop events was 86.46% ± 12.55%. The accuracy was higher than 91% for 5 out of 8 subjects. The algorithm also indicated the onset of sub-components of nursing activities for the majority of the subjects. The results of this study suggest that the presented algorithm may be useful in identifying transition points of human activities recorded with accelerometers.
5.2 Introduction

Poor hand hygiene practises by hospital staff have been linked to Hospital Acquired Infections (HAIs) [1]. HAIs are responsible for approximately 100,000 deaths each year in North America [4, 5] and cost 4.5 billion to the health care system [6, 4]. Several studies [8, 9, 7] have shown that hand washing is the most important single intervention to prevent HAIs.

At Toronto Rehabilitation Institute (TRI) in Canada, we are developing technologies to help hospital staff to remember to wash their hands. Our team developed a system that records all hand hygiene actions performed with wearable alcohol gel dispensers and stationary alcohol gel or soap dispensers. It also detects if caregivers enter or leave monitored areas around patient beds (patient zones). Combining both the zone status and hand hygiene activity information, the system decides on whether hand hygiene is necessary and prompts the user accordingly [49]. We are enhancing this system by providing it with the ability to identify any nursing procedure that requires hand cleansing within the patient zone such as aseptic procedures and activities where there is a risk of body fluid exposure. This paper describes a method for identifying the occurrence of these nursing procedures.

5.3 Background

In our previous work, we investigated the possibility of using wearable accelerometer sensors to identify nursing activities in the infection control context [64]. Eight subject nurses participated in our study and the task was to identify six different nursing activities that usually occurred within patient zones. The automated system was compared to a trained observer who recorded the start and stop time of each activity. We processed the data offline and achieved overall 85% recognition accuracy. We are enhancing this system to automatically segment the stream of the acceleration data to detect the start and stop
time of each nursing activity. This will eventually enable our system to become more suitable for real-time applications, where the nursing activities and the corresponding start and stop time of each activity must be recognized in real-time.

Automatic data segmentation seems to be a subject that is mostly ignored in the majority of the past research that focused on recognizing human activities using accelerometers. In these studies continuous acceleration data was segmented manually by either a trained observer [83, 56, 84, 60, 85, 76, 86, 74, 75, 57, 51, 58] (First phase in [56] or the subjects themselves (self-reporting) [55, 50, 56, 61, 73, 53] (Second phase in [56]). This data segmentation was necessary to divide a portion of the recorded signal to train the classifiers that used a supervised learning approach [87, 66]. In this method the classifiers are trained using some examples of manually segmented activities where the identity of the activity is already known. Once the classifier is considered trained, the rest of the data can be analyzed automatically and in the studies is used to test and validate the classifier.

Data segmentation is a difficult task even when done manually. Furthermore, it has also been reported that the acceleration data corresponding to the task transition segments contaminates the data, resulting in mislabelling the human activities [86]. To overcome this problem, some researchers trimmed and discarded up to 10 seconds of data within the start and stop of each activity [50, 88]. Others used additional sensors such as microphones worn at the dominant hand to record environmental sound intensity [77] and RFID tags attached to the surrounding objects [59] to mark the onsets of human activities to segment the data.

The focus of this paper is on the development of an algorithm to automatically detect the onset of nursing activities recorded from accelerometers without the need for additional sensors. Once the onsets of activities are identified, suitable machine learning algorithms can be used to recognize the nursing activities, which is not the focus of this research.
5.4 Method

Our segmentation algorithm is based on an adaptive signal processing technique, where the original signal is first processed by a predictor filter and then the signal is compared with its resulting version. If a sample of the original signal is significantly different from its predicted version, this suggests a point in time when the signal statistics (e.g. mean, standard deviation) change. This point is called a non-stationary point. We hypothesize that non-stationary points processed by a predictor filter can be used to indicate the onset of nursing activities.

5.4.1 Datasets

We used a dataset previously recorded from 8 subject nurses in our earlier study [64]. We considered only the dataset that included a continuous data of combined trials of 6 simple nursing activities: 1) talking to a patient, 2) checking on vital signs, 3) replacing an Intravenous (IV) bag, 4) checking on blood sugar, 5) placing a bedpan under the patient, and 6) giving oral medication to a surrogate patient. Data were recorded by a single sensor attached to the back of each nurse. Each nurse performed the nursing activities at their own speed and in their usual way habit and a trained observer quietly annotated the start and stop of each activity. We included 5 seconds before the start time of the first activity (Talking) and after the stop time of the last activity (Giving oral medications) to better validate the performance of the algorithm. A trained observer carefully compared the onsets of the nursing activities detected by the algorithm against the time-stamped recorded video data. The following describes the segmentation algorithm, which is based on adaptive filter theory.
5.4.2 Adaptive Filter

In signal processing, traditional filters are used to remove unwanted frequency components, (noise) in the signal. For example in North America, a 60 Hz notch filter (50 Hz in Europe and most other parts of the world) is used in electrical devices to remove the unwanted power line noise. In the digital domain, filters use a set of fixed coefficients. These coefficients create a frequency response for the digital filter. When a digital input signal is processed by a digital filter, the resulting output digital signal does not contain the frequency components restricted by the digital filter.

Digital filters with fixed filter coefficients are capable of removing noise as long as its frequency characteristics do not change over time. In applications where noise frequency characteristics change over time, or they overlap with the original signal’s frequency characteristics, it is recommended to use an adaptive filter. In an adaptive filter the filter coefficients are updated constantly, changing the filter’s frequency characteristics in real-time to remove the noise.

Figure 5.1 illustrates a block diagram of a basic adaptive filter. The adapting algorithm compares the input signal with a desired signal and tries to change the filter coefficients to minimize the error between both signals. Adaptive filters can be arranged in four basic configurations to perform different tasks namely, system identification, inverse modelling, prediction, and noise cancellation [62].
In this study we used an adaptive filter as a predictor filter. As illustrated in Figure 5.2, the predictor filter is placed in series with a delayed version of the original input signal and the original signal also serves as the desired signal. The delay is chosen to make the reference signal uncorrelated with the input signal at any time instant [89]. The filter estimates the current output sample of the original signal using only a limited number of the past samples. When the current estimated sample is significantly different from the actual sample, this indicates the point when the signal statistics (e.g. mean, standard deviation) change and the signal becomes non-stationary. In this research we hypothesize that the non-stationary points processed by the adaptive predictor filter may indicate the onset of each nursing activity. We used the Recursive Least Squares (RLS) adaptive algorithm [62, 89] for its fast convergence. The RLS algorithm has been successfully used previously in many applications including noise cancellation from an accelerometer embedded in a bus under a performance test [90], segmentation of vibroarthrographic (VAG) signals [91], and segmentation of electromyographic (EMG) signals during sleep studies [92].

5.4.3 Adaptive segmentation based on RLS

Moussavi and Rangayyan [91] used RLS algorithm to segment non-stationary VAG signals into locally stationary segments. We used the same approach but adjusted the filter
parameters to segment accelerometer signals. The RLS filter parameters are the input
delay, the filter order, and forgetting factor, $\lambda$ ($0 < \lambda \leq 1$). $\lambda$ is a weighting factor
that gives more weight to the most recent error value [62, 89]. Here we briefly explain
Moussavi’s algorithm:

- Arrange an adaptive filter as a predictor filter, set the delay, the filter order, and
the forgetting factor $\lambda$ and use the RLS algorithm to update the filter coefficients.
- Initialize the RLS algorithm.
- Calculate the squared Euclidean distance between the two adjacent filter coefficients
vectors at each sample and store as error vector $e(n)$

$e(n) = \|w(n) - w(n - 1)\|^2$, \hspace{1cm} (5.1)

where $w(n)$ is the filter coefficients vector of the RLS algorithm at time $n$.
- Set a predefined threshold as three times the standard deviation of the $e(n)$ vec-
tor processed over the signal. Compare each element of the $e(n)$ vector with
the threshold and store the results as ”Primary Segment Boundaries”, $PSB =
[a_0, a_1, a_2, \cdots, a_p]$, where $a_0 = 0$.
- Since a segment with a very few samples does not provide useful information about
the signal, define a constant as the minimum acceptable length of the signal ($L_{min}$).
- Compare each element of PSB vector with $L_{min}$. If $a_i - a_{i-1} \geq L_{min}$, $i =
1, 2, \cdots, p$, keep $a_i$ as the non-stationary point of the segment and check the next
element. If $a_i - a_{i-1} \leq L_{min}$, remove $a_i$ and continue.
- All the remaining $a_i$ points from the previous step are the final segment boundaries.
While Moussavi used delay=7, filter order=5, and $\lambda=0.98$ to process VAG signals, it was not clear if these parameters were suitable to process acceleration signals recorded from human activities. To our knowledge there is currently no report on the proper choice of these parameters. Therefore, we iteratively explored different values that resulted in optimizing the accuracy for all subjects, noting that filter order must be low enough to make sure we detect transitional changes at the input and at the same time achieve fast convergence [91]. All the necessary software was written in MATLAB® (The MathWorks Inc. Natick, the U.S.A.). Preliminary results suggested that delay=1, filter order=5, and $\lambda=0.98$ were suitable in our application. We also chose the predefined threshold to be 2 times the standard deviation of the $e(n)$ vector, because the preliminary tests revealed that setting a threshold higher than this may result in missing the activity onset points. We calculated the time difference between the stop time of a nursing activity and the start time of the next activity for all subjects. We found that the minimum time difference was about 2 seconds and therefore we set approximately 2 seconds worth of data (88 samples) as the minimum acceptable length of the signal segment, $L_{min}$. This ensured that the onsets of consecutive activities are not missed.

Comparing the preliminary results of the segmentation algorithm to the video clips revealed that the majority of the activity onsets happened when at least 2 of 3 axes detected a change point not more than a second apart. Any change point detected in any axis is the result of an activity or change in the body posture in the same axis. We assumed that the activity duration and the nurse’s posture does not change significantly in any 2-axis plane within a vicinity threshold that was set to one second. Therefore, we assumed that the change points detected by at least 2 accelerometer’s axes not more than a second apart are the results of the same activity.
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Figure 5.3: An example of automatically detected nursing activities onsets for Subject7. The solid lines mark the onsets of start and stop of each activity, validated by time-stamped video data. An example of detected onsets of the sub-activities is shown for the bedpan activity, marked by dashed lines.

Figure 5.4: The bedpan activity for Subject7 is zoomed. Solid lines mark the start and the stop of the activity and the dash lines mark the onsets of the sub-activities. A: Put the bedpan on the tray; start rolling the patient. B: Start grabbing the bedpan from the patient tray. C: Start positioning the bedpan under the patient. D: Start replacing the blanket. E: Finished replacing the blanket; end of the bedpan activity.
5.5 Results

Figure 5.3 illustrates an example of results of the segmentation algorithm on acceleration data for Subject7. The circles mark the non-stationary points, $a_i$, as described in Section 5.4.3. Each solid vertical line indicates a point in time when at least 2 axes non-stationary points fall not more than a second apart. These points are considered the onsets of the nursing activities and they were plotted after being carefully validated by the time-stamped video data. For better illustration purposes, we showed only the onsets of the start and stop time of each major nursing activity.

Each complete nursing activity consists of smaller procedures or sub-activities. For example, placing a bedpan under the patient (assuming the bedpan is already near the patient), requires the nurse to remove the patient’s blanket, roll the patient to the opposite side of the bed. While keeping the patient in this position with one hand, the nurse needs to place the bedpan under the patient with the other hand, roll back the patient, and finally cover the patient with the blanket. As an example of sub-activities in Figure 5.3, we plotted the detected bedpan sub-activities. These events are marked by the dashed lines. Figure 5.4 illustrates a zoomed version of the bedpan activity and illustrates its sub-activities in details. These points are marked by dashed vertical lines after being carefully validated by the time-stamped video data. It can be seen that the algorithm correctly marks the onset of major sub-activities that constitute a complete bedpan activity.

Each major nursing activity includes a start and stop event. Therefore, we calculated the accuracy of the algorithm on 12 major event detections per subject. Table 5.5 summarizes the processed results for all subjects. The success rate accuracy for each subject is calculated by dividing the number of correct detected events per subject by 12.
Table 5.1: The algorithm performance in detecting the start and stop events of each nursing activity. The accuracies above 90% are indicated in bold

<table>
<thead>
<tr>
<th>Subjects</th>
<th>Number of predicted Start and Stop events</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Subject1</td>
<td>9</td>
<td>3</td>
</tr>
<tr>
<td>Subject2</td>
<td>8</td>
<td>4</td>
</tr>
<tr>
<td>Subject3</td>
<td>12</td>
<td>0</td>
</tr>
<tr>
<td>Subject4</td>
<td>9</td>
<td>3</td>
</tr>
<tr>
<td>Subject5</td>
<td>11</td>
<td>1</td>
</tr>
<tr>
<td>Subject6</td>
<td>11</td>
<td>1</td>
</tr>
<tr>
<td>Subject7</td>
<td>12</td>
<td>0</td>
</tr>
<tr>
<td>Subject8</td>
<td>11</td>
<td>1</td>
</tr>
<tr>
<td>Overall</td>
<td>83</td>
<td>13</td>
</tr>
</tbody>
</table>

5.6 Discussion

In our study the nurses performed the activities based on their own habits. Therefore, the detected onsets of nursing sub-activities may or may not appear in all subject’s acceleration signals. For example, a few nurses put an empty IV bag on the bed beside the patient before installing a new one. Other nurses chose to put the empty IV bag on the bedside table that was steps away from the patient. These variations are even more noticeable comparing Subject1 to Subject4 who cared for a manikin patient [64]. Whether the nursing sub-activities were legitimate or not is quite subjective. Therefore, we ignored the detection of nursing sub-activities and we did not report the accuracy results for these activities even though careful inspection of Figure 5.4 suggests that the algorithm is capable of marking the onsets of nursing sub-activities. This is also consistent with our previous work when we did not breakdown each nursing activity of interest into smaller sub-activities but we considered each activity as a whole to extract
Figure 5.5: Bedpan activity for Subject6. The solid lines are the detected events by the algorithm. The observer’s time-stamp for the start of the activity is shown by the dashed line. A: Go to retrieve the bedpan. B: Start removing the blanket. C: Start positioning the bedpan under the patient. D: Start replacing the blanket. E: Finished replacing the blanket; end of the bedpan activity.

classification features [64]. Techniques to estimate the main activity from a sequence of sub activities will be the focus of a future study.

Owing to the subjective nature of marking the start and stop time of events, these points did not necessarily agree with the observer’s time stamp. Careful video clip inspections confirmed that for the correctly detected events, the algorithm marked the exact time of the major change in the nursing activity. For example Figure 5.5 illustrates the bedpan activity for Subject6. The dashed vertical line shows the start of the activity as marked by the observer at the time of data collection. It can be seen that the algorithm marked the time when the nurse stepped out to retrieve a bedpan (point A) and it also marked the time when the nurse started removing the blanket (point B). The observer ignored point A and instead chose point B as the start of the bedpan activity. In this example the time difference between the observer’s time stamp and the algorithm’s time stamp for point B is about 0.4 second.

The proposed algorithm requires no training to detect the onset of activities and
it detects a major change in the acceleration signals in real-time. This suggests that
the algorithm has the potential to be implemented in applications where activity onset
detection is required in real-time. In contrast, the lack of proper training implies that
the algorithm does not differentiate among relevant and irrelevant events. For example
few nurses performed extra movements while performing nursing sub-activities such as
bending over the bed or moving to the other side of the bed to raise the head of the bed
prior to giving oral medication. These extra movements were detected by the algorithm
as event onsets. Although we did not consider nursing sub-activity events in this study,
our future challenge will be training proper machine learning algorithm to recognize the
main events and ignore the irrelevant ones.

Although we did not test the ability of our algorithm to detect the onset of general
posture transitions (e.g. sit-to-stand) in human activities we expect that the proposed
algorithm may also be helpful where other algorithm such as a hierarchal binary tree
fail [86].

Unlike Moussavie et. al. who chose a threshold of 3 times the standard deviation of
the error vector \( e(n) \), our experiment showed the algorithm did not detect the onset of
the certain activities for a few subjects that required a small change in body posture. We
had to lower the threshold to 2 times the standard deviation to better identify the activity
change for all subjects. This is probably due to slow change in the acceleration signal
in nursing activity transitions compared to VAG signals. Therefore, depending on the
application the threshold value should be adjusted to produce a higher event recognition
rate.

The proper choice of RLS filter parameters is also very important. For example a
filter with a long delay may miss a fast transition point. While the chosen RLS filter
parameters in this study showed acceptable accuracy for all the subjects, we expect that
fine-tuning these parameters to each axis of the accelerometer signal per individual nurse
may lower the number of false negatives, resulting in increasing the recognition accuracy.
5.7 Limitations

The proposed algorithm depends on both a preset threshold and the proper choice of RLS parameters, which is a problem common to all the applications that implement the RLS algorithm for segmentation. We estimated these parameters by trial and error over the available dataset and sample size. These parameters are directly related to the nature of the signal and may need to be adjusted for other applications where activities and posture transitions happen at different speeds. Therefore, the minimum segment length parameter, $L_{min}$, should also be adjusted accordingly. We plan to do more trials with a bigger sample size to validate the choice of these parameters.

Currently, the threshold is related to the standard deviation of the signal, recorded for the complete trial and is therefore only suitable for offline data analysis. In real-time applications this threshold may need to be adjusted dynamically by monitoring the change in the standard deviation of the signal over time.

5.8 Conclusion

We introduced an algorithm to automatically identify the start and stop time of nursing activities recorded by accelerometers without the need of any training set. The algorithm is based on an RLS adaptive predictor filter. The algorithm identifies the onsets of the nursing activities when at least 2 of 3 axes show significant changes in the acceleration signal not more than a second apart. The overall accuracy of the algorithm for a total of 96 events performed by 8 subjects was $86.46\% \pm 12.55\%$. The accuracy was higher than 91% for 5 out of 8 subjects. The algorithm also indicated the onset of nursing sub-activities for a majority of the subjects. The results of this study suggest that this algorithm may be useful in marking the transition points of human activities recorded by accelerometers.
Chapter 6

“My Five Moments for Hand Hygiene” - A Novel Risk-Based Approach

The material presented in this chapter is excerpted in entirety from the following submitted journal article:


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Contribution of authors: K. Momen wrote the manuscript, and developed and validated the model. G. R. Fernie, reviewed the manuscript, and led the research project.

Chapters 3, 4, and 5 described how accelerometers may be used to identify examples of nursing activities. Once the sequence of nursing activities are identified, it may be possible to relate them to their corresponding WHO “five moments for hand hygiene”. Implementing this information into the logic of an intelligent hand hygiene reminder
system may help caregivers cleanse their hands as required by WHO hand hygiene model, which is believed to reduce the rate of HAI.

Although 100% hand hygiene compliance based on the WHO hand hygiene guidelines are highly recommended, it is not always feasible to implement this into today’s caregivers’ busy schedules. For example McArdle et. al. [22] has reported that caregivers need to allocate approximately 230 minutes for hand hygiene per patient per day in an ICU unit. This suggests that either 100% hand hygiene compliance is not achievable or caregivers need to allocate less time for caregiving procedures, which is not desirable. It seems that there is an opportunity to optimize caregivers time and help them to achieve the best possible hand hygiene compliance without sacrificing caregivers performances.

One way of optimizing the allocated time for hand hygiene is to include the risk of infection transfer in the hand hygiene model. Such a risk-based model would emphasize to cleanse hands when there is a high risk of infection transfer to the patient and indicate less urgency for hand washing when the risk of infection transfer to the patient is low. For example, taking a blood sample or any invasive procedure is considered high risk activity, while checking on patient vital signs may be considered low risk.

In this chapter I explain a model to study the risk of infection transfer by the hands of a caregiver upon leaving a patient, given the hand hygiene compliance rate. I modified the WHO “My five moments for hand hygiene” model by associating three levels of risks (Low, Medium, and High) to each moment in the model. For simplicity I used the Canadian version of the hand hygiene model that considers the WHO Moment4 and Moment5 as one moment. The presented model may help to study the mechanism of infection transfer around the patient and his/her surroundings provided that the data is collected based on the WHO or its Canadian version hand hygiene model. This model may also optimize the hand hygiene prompts if implemented into an electronic hand hygiene reminder system. Last but not the least, the model may be used as an epidemiological model to predict a possible infection outbreak if trained by proper data.
Chapter 6 - “My Five Moments for Hand Hygiene”

6.1 Summary

We developed a mathematical model to estimate the risk of cross-contamination based on the World Health Organization (WHO) guidelines for hand hygiene (HH). For simplicity, we simulated the results based on the Canadian version of the WHO guidelines (Four moments for HH). We modelled the moments of caregiving process as a Finite Markov Chain. We assigned three levels of risk of transmission of infection (low, medium, and high) to each moment of HH to construct an 18-state Markov Chain. The transition probabilities from the lower-risk to the higher-risk states represented the total risk of cross-contaminations. For the simulation we assumed that the transition probabilities were equal to the proportion of encounters of the caregivers with HH moments. Transition from higher-risk to the lowest-risk level was dependant on the probability of HH. Based on this assumption, we used recently published data to calculate the transition probabilities. The results of the simulation showed that the high-risk of cross-contamination decreases exponentially by frequency of HH. We also found that if the caregiver enters the room with high-risk of transferring infection to the current patient, given our assumptions in this study, only 55% HH is capable of reducing the risk to the lowest level and help to prevent the next patient from acquiring infection. The model is also capable of simulating the effects of the imperfect HH on the risk of cross-contamination.

6.2 Introduction

Hospital Acquired Infections (HAIs) are an increasing global concern affecting hundreds of millions people around the world [1, 2]. It is estimated that about 1.4 million patients have HAIs at any given time [3]. In North America HAIs are believed to be responsible for 100,000 patients deaths each year [4, 5] and a big economic burden on the healthcare systems [4, 6]. It is believed that better hand hygiene (HH) practise by caregivers is the single most effective intervention to reduce the rate of HAIs [7].
Several mathematical models have been proposed to study the impact of different risk factors, and interventions such as HH compliance rate on HAIs rates [93, 94, 95, 29, 27, 96, 97]. These models help to predict an infection outbreak if the risk factors reach a critical point. The results of these simulations are useful to determine the major risk factors in HAIs under specific circumstances and suggest what interventions are necessary to control a possible outbreak before it happens.

The gold standard in measuring HH compliance rate is direct observation [98, 44]. In the past, the report for observational HH compliance rate did not follow a specific standard [47, 13]. In order to promote better HH and standardize the HH training, observation and performance reporting in all healthcare setting around the world, The World Health Organization (WHO) has created set of guidelines, known as “My five moments for hand hygiene” [44]. The WHO guideline mandates all caregivers to wash their hands in 5 moments namely,

1) before patient contact (M1), 2) before an aseptic task (M2); 3) after body fluid exposure risk (M3), 4) after patient contact (M4) and 5) after contact with patient surroundings (M5). Each moment of HH in the WHO guidelines is referred to as an HH opportunity. The HH compliance rate is measured by dividing the number of HH actions by the number of HH opportunities within the observation period [98].

Recently, infection control researchers started to report handwash compliance data based on the WHO guidelines [99, 100, 101]. In Canada, the Ontario Ministry of Health and Long-Term Care (MOHLTC) has locally adapted the WHO guidelines by combining the moments M4 and M5 [102]. Since August 30, 2009 all hospitals across the province of Ontario are required by law to report their HH compliance rates based on the new Ontario MOHLTC HH guidelines.

In the past research, mathematical models were developed to study infection control in a hospital ward, the whole hospitals, and communities [96]. In the absence of general WHO guidelines, the mathematical models were not designed to benefit from the
observation of caregivers’ practises [7]. While more data are now collected and reported using WHO guidelines to study the HH compliance in both time and space [44], it seems that we need to start developing new mathematical models to benefit from the data collected based on WHO guidelines. This will further enable us to study the mechanism of infection transfer at room level while observing caregiver’s practises at the point of care.

The objective of this research is to develop a model based on the WHO guidelines to estimate the risk of transferring infection from one patient to another patient by caregiver’s hands at room level. More specifically, we are interested in predicting the risk of infection transfer when the caregiver finishes the care activity and he or she is about to leave the current patient. For model simplicity we considered the Canadian version of the WHO guidelines.

6.3 Method

When a caregiver enters a room he or she carries a certain level of risk of transferring the infection to the patient. The caregiver accumulates the risk of transferring the infection to the next patient if he or she misses one of the M1 to M4 HH opportunities [44]. In order to simplify the model we assumed that a single handwash action reduces the risk of the infection transfer to the lowest level at which the risk of transferring infection to the next patient is negligible. Based on these assumptions we modelled the above scenario by a Finite Markov Chain with absorbing states [103] at the exit. The Finite Markov Chain is a mathematical system composed of finite number of states. The system undergoes transition from one state to another and the next state is only dependant on the current state but not the past states.

We first constructed the model by a 6-state Markov Chain. The chain starts with an entry state, followed by four states representing M1 to M4 moments, and ends with an exit state. We introduced three levels of risks as “Low”, “Medium” and “High” to each
Figure 6.1: Complete model based on 18-states Finite Markov Model with an example of the transitions. \( p_\lambda \) is the probability of HH that brings the risk level to the lowest level at any given states.

We assumed that the probability of being in a specific state at any given time is only dependant on the probability of being in the previous state to satisfy the Markov Chain properties. This assumption is consistent with HH practise in real life; when the hands
of the caregivers are dirty, a single perfect HH action will change the state of the hands to clean state, regardless of their cleanliness or dirtiness before performing HH.

We also assumed that the transition probabilities do not change overtime (stationarity assumption). This assumption is also similar to real life examples; the majority of risk factors that contribute to increase risk of cross-contamination do not change over time significantly. For example, the patient condition does not change in a very short period of time. The frequency of the nursing activities although may change in short period of time, it has always been reported as an average over specific time period, such 24 hours [100, 101].

All states except the exit states are called transient states, \( t_i \), \( i = 1, 2, \ldots, 5 \) and all the exit states in this model are defined as absorbing states, \( a_j \), \( j = 1, 2, 3 \). The absorbing states are the states that once the system enters them, it is impossible to leave these states. Therefore using Finite Markov Chain theory [103] we can calculate the probability of entering to any absorbing exit states provided that we started from specific transient state such has entry states.

The total risk of transferring infection to a patient is the contribution of different risk factors including hospital ward, time of day, day of week, professional category of health care worker, type of patient care, frequency of the activity, the rate of contact between patient and caregiver, the condition of the patient, and the environment [97, 104, 105]. In this model the total risks of transition from one state to another are equal to the transition probabilities. In this work we did not calculate the total risk from individual risk factors and to our knowledge there is currently no report on how to reliably perform this calculation [44]. Instead, we estimated the actual \( P_{ij} \) transition probabilities based on the frequency of HH moments, which is directly proportional to the caregiver-patients contact rate. This parameter has been used as a major risk factor in the previous mathematical models [94].

We estimated the frequency of the HH moments based on the recent published
data [101]. The authors reported that some of the M1 contacts were hidden from the observers and therefore we expected this information was not reliable for our study. To overcome this, we assumed that upon entry to the room there is equal probability to visit any of M1, M1’, and M1”. After touching the patient or the patient’s environment, the caregiver may transfer to any of M2, M3 and M4 states in which a HH action is required. If a HH action is missed, depending on the total risk involved (transition probability), the caregiver status is transferred to a higher risk level for that specific moment. Based on the reported data, 6% of the opportunities were M2, and 12% were M3. Therefore, starting from M1 we can assume that the probability that we next encounter an M4 opportunity is 82%. As the data was reported in general for specific moment (e.g. M2=6%), we equally divided the probability of transferring between the current risk level and the higher risk-level for the same specific moment (e.g. M2’→M2’=3%, and M2’→M2”=3%) to cover all possible transitions even within the specific risk level. For simplicity in this work we also assumed that none of the activities transfer from low risk level directly to high risk level although this is an assumption that may not be credible in practise.

We assumed that the caregivers’ hands are the source of infection transfer. Therefore, in our model the only way to transfer from higher risk level to a lower risk level is performing a HH action. We also assumed while all HH actions are 100% effective, the caregivers wash their hands with probability of \( P_\lambda \) that is the only transition path from higher risk states to the lowest risk state (Figure 6.1). In contrast, in the absence of HH the caregiver’s risk status increases and it is advanced to the associated risk level with probability weight of (1 – \( P_\lambda \)).

The complete probability transition matrix of the proposed model is illustrated in Table 6.1. Each cell in the table, \( P_{ij} \), is the probability of going to state \( j (j = 1, 2, 18) \) given that we are currently in state \( i (i = 1, 2, \cdots 18) \). In this table all the transient states are written first, followed by the absorbing states. As all the elements of the transition matrix are probabilities, the sum of each row is equal to one. The transition probabilities
for the example shown in Figure 6.1 are shown in bold.

The Markov chain’s fundamental matrix of the above model is defined as [103]:

\[ F = (I - Q)^{-1} \]  \hspace{1cm} (6.1)

where \( F \) is the fundamental matrix of the model, \( Q \) is a 15x15 matrix of transient states and \( I \) is a 15x15 identity matrix. The probability that we will eventually be absorbed in an absorbing state \( a_j \), given being at present transient state \( t_i \), is the \( ij^{th} \) element of the matrix \( P \) [103]:

\[ P = (I - Q)^{-1}.R \]  \hspace{1cm} (6.2)

where \( R \) is a 15x3 matrix of absorbing states. We calculated matrix \( P \) for probability of HH, \( P_\lambda = 0, 0.1, 0.2 \), , , 1. We used MATLAB® (The MathWorks Inc. Natick, the U.S.A.) to calculate the results.

### 6.4 Results

Table 6.2 illustrates Matrix \( P \) calculated using Equation (2) for HH probability of 0%, 20%, 55%, and 100%. \((P_\lambda = 0, 0.2, 0.55, 1)\). Matrix \( P \) is 15x3 and predicts the probability of starting from any transient states and falling into any of the absorbing states. In this study we were interested in predicting the probability of falling into one of the exit risk levels, given starting from any of entry risk levels. Therefore only the three rows of matrix \( P \) related to this information are shown.

Figure 6.2 shows the probability of exiting with high-risk level versus the probability of handwash, given entering the room with high risk level. This plot is generated by calculating the \( ij^{th} \) element of the matrix \( P \), for \( i= \) high-risk entry (Enter”) and \( j= \) high-risk exit (Exit”) for probability of HH, \( P_\lambda = 0, 0.1, 0.2 \cdots 1.0 \).
Table 6.1: The complete probability transition matrix of the proposed model. *Q* denotes transient states and *R* denotes the absorbing states. $P_a$, $P_m$, $P_s$, $P_d$, $P_4$ are the probabilities of being in $M_2$, $M_3$, $M_4$ states respectively.

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</table>

$P_a$, $P_m$, $P_s$, $P_d$, $P_4$ are the probabilities of being in $M_2$, $M_3$, $M_4$ states respectively.
Table 6.2: Calculated probabilities (%) of being absorbed in exit states, given starting from any entry state. The medium risk states are shown by prime symbol, and high risk states are shown by double prime symbol. $P_\lambda$ is the probability of hand hygiene.

<table>
<thead>
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<td>55 32 13</td>
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<td>20 29 51</td>
<td>55 32 13</td>
<td>100 0 0</td>
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<td>0 0 100</td>
<td>20 23 57</td>
<td>55 31 14</td>
<td>100 0 0</td>
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Figure 6.2: The probability of leaving the patient with high-risk status, given visiting the patient with high-risk of cross contamination decreases exponentially by increasing the rate of HH.

### 6.5 Discussion

In order to confirm the results of simulation we start with the results of 0% and 100% HH rate ($P_\lambda = 0$ and $P_\lambda = 1$) that are easier to predict.

In theory if a caregiver enters the room and does not perform HH during caregiving activities before leaving the current patient ($P_\lambda = 0$) we expect the risk of transferring the infection to the next patient to be high, regardless of the caregiver’s risk level upon
entering the room. Table 6.2 shows that if the caregiver enters with low-risk level, depending on the risk levels for the upcoming nursing activities and performs certain caregiving activities, there is 0% chance that the caregiver leaves the room with low-risk level. If the caregiver enters with high-risk level, it is impossible to leave the room with low risk or medium risk and the caregiver leaves the room with high risk of infecting the next visiting patient.

In contrast, if the caregiver practises 100% HH, it is impossible to leave the patient with medium or high risk of transferring the infection to the next patient. Therefore, the probability of cross-transmission to the next patient is quite low and it is consistent with literature that suggests HH decreases the risk of cross-contamination [7].

For simplicity we used a heuristic approach to estimate the optimum HH rate. In this approach we increased the HH rate from 0% to 100% and observed at each level of HH the risk of cross-contamination at the exit is low, given the caregiver enters the room with high-risk level of cross-contamination. For example, when HH rate of 20% is introduced to the model, the risk of being in a high-risk exit state is still higher than those of medium and low risk, regardless of the potential risk upon entry. Referring to Table 6.2, $P_\lambda = 55\%$ suggest that if caregiver enters the room carrying high-risk status but achieves only 55% HH, the chances of leaving the room with high-risk status is only 14%, which is less than half of the chance of leaving the room with medium risk and about 4 times less than leaving the patient with low-risk level. These results are consistent with the latest study that suggests HH rate of greater than 53.4% is needed to keep the basic reproductive number, $R_0 < 1$ for settings where there is a high caregiver-to-patient infection transmissibility [94]. $R_0$ is the average number of secondary cases that are generated by a single primary infected case with no infection control intervention in place. If $R_0 > 1$ there will be new cases of infection and therefore there will be an infection outbreak and $R_0 < 1$ implies that the infection will eventually die out. In this work our terminology of low-risk, medium-risk, and high-risk of infection transfer is
analyses to $R_0 < 1$, $R_0 = 1$, $R_0 > 1$ respectively. Although these are different concepts the comparison is given as an example.

Figure 6.2 suggests that the probability of leaving the current patient with high risk of cross-contamination decreases exponentially by increasing the level of handwash even if the caregiver visited the current patient with high risk status. Therefore, the curve suggest that increasing HH level to a certain level (50%-60%) rapidly decreases the risk of cross-contamination and HH level beyond this level has little effect. Although we used a risk-based approach in our model and we studied the cross-contamination at the room level, these results are similar to previous work [94, 95].

The proposed model is flexible in the use of guidelines and the risk levels. For simplicity we presented the model based on the adapted Canadian version, “Your 4 moments of hand hygiene”. This model can be extended to the WHO “My five moments for hand hygiene” by introducing the 5th state, M5, including its associated risk levels into the model, and calculating the transitions matrix accordingly. Moreover the risk levels associated with each moment can be reduced to two (Low, High) or expanded (e.g. Low, Medium-Low, Medium, Medium-High and High) depending on the settings and the researcher’s understanding of these risk levels. We presented common possible scenarios for the transition from one moment to another and within the risk levels. Depending on the application, some of the transitions may not even exist or additional transitions may need to be added to the model. For example, touching a patient with MRSA in an M3 event immediately transfers the risk from low to high. While the calculation remains the same, the challenge is to estimate the transition probabilities and fit the model with realistic data.

In our proposed model it is possible to simulate the effects of imperfect HH. To include this, all or some of the transitions from high-level moments can be directed to a lower level with probability of $P_{\lambda'}$. For example in a 3-level model, $P_{\lambda'}$ will bring the, risk level to medium and $P_{\lambda}$ will bring the risk from medium to low level. The challenge is to
estimate a correct rate of the imperfect HH from observational data as it has been shown this is dependant on the type of the hand cleansing agent, the type of the infection, the technique of handwash and the duration of the process [94].

Pittet et al. [104, 21] observed lower HH compliance in high-risk activities during their studies. Our model can be useful if implemented in intelligent HH reminder systems [18] due to its capability of identifying high-risk moments. To achieve this, our proposed model may be combined with an intelligent system that aims to identify nursing activities [64]. Once the high-risk nursing activities are identified using these technologies, the model can help the HH reminder system to emphasize on performing HH in high-risk exits status.

It has been reported that 100% handwash compliance needs up to 230 minutes per day per patient in certain settings [22], which may not seem feasible to achieve in practise. Therefore if an intelligent HH reminder system is used in such settings the caregivers will receive a high number of prompts to perform HH. A high incidence of seemingly irrelevant reminding prompts may lead to important prompts being ignored. Therefore, a risk-based model such as the one we presented may help current technologies to remind the caregivers wash their hands when it is absolutely necessary. This may help caregivers to achieve optimum HH during their busy schedule.

6.6 Limitations

In this study we had to make many assumptions in order to estimate the parameters of the model. The key requirement of the model is to calculate the probability transition matrix from which the fundamental matrix is then computed. To our knowledge there is currently no report on how to compute these parameters based on the WHO guidelines. We based our simulation only on the frequency occurrence of each HH moment reported on the recent work 21. However, this is only one of the risk factors that constitutes the
total risk. One possible way of calculating the total risk from the individual risk factors is to use Failure Mode and Effects Analysis (FEMA) [106] to consider the weight of each factor that constitutes the total risk. This is the subject of our current research.

In our approach we used the term low-risk status to indicate the desired condition of the caregiver after leaving the patient to reduce the risk of cross-contamination. It should be noted that low-risk condition does not mean no-risk condition. In a low-risk condition there is still a threat to the patient’s safety. However, it is considered low. Therefore, the terms low, medium and high need to be defined accordingly depending on the situation.

6.7 Summary and Conclusions

To our knowledge this is the first study that aims to estimate the risk of cross-contamination based on the WHO guidelines for HH. We assigned three levels of low, medium, and high levels to each moment of HH based on the Canadian version (four moments of HH). We constructed an 18-state Finite Markov Chain model and we computed the Markov Chain’s Fundamental Matrix. For simplicity, we assumed that the total risk of cross-contamination was only dependant on the fraction of encounters that caregivers had with any M1, M2, M3, and M4 moments. This allowed us to estimate the transition matrix based on the recent published data. By simulation we found that the high-risk of cross-contamination decreases exponentially by frequency of HH. We also found that if the caregiver enters the room with high-risk of transferring infection to the current patient, given our assumptions in this study, only 55% HH is capable of reducing the risk to the lowest level and helping to prevent the next patient from acquiring infection.
Chapter 7

Discussion and Conclusions

7.1 Summary of contributions

In this thesis I developed and presented essential elements of a potential nursing-activity-based hand hygiene reminder system. The aim of such system is to monitor caregiving activities in real-time and help the caregivers remember to cleanse their hands when it is necessary.

Modifying the hardware of an inexpensive game controller, I was able to develop a low-cost, completely wireless, accelerometer-based data acquisition system to collect raw acceleration data from examples of nursing activities. The system requires a personal computer running the Linux operating system. The wireless connectivity is established via a Bluetooth link. Up to seven wireless accelerometer sensors can be connected to each USB adaptor connected to the personal computer.

At the time of developing this system, the competing commercially available system in the market required the accelerometer sensors to be hard wired to a central module worn and carried by the user to enable the central module to transmit the data wirelessly to the data-logging computer. This would create discomfort for the participants and requires more time to prepare the participants to wear the sensors, secure the wires, and
possibly limiting the participant’s range of motion. Moreover, the cost of the system that I developed was at least 40 times less than the cost of the nearest competing commercially available system at the time of the development, resulting in saving lab resources during this study.

Another advantage of the developed system is that it makes the time-stamping and signal segmentation easy; an unmodified game controller was used to time-stamp the start and stop of each activity. Two buttons were assigned to record the start and stop of each activity, and each unused button on the controller was assigned to a specific nursing task. As this unmodified controller was wirelessly connected to the same data logging computer, no manual signal alignment was required. The hardware that I developed in the first phase of this work can be used as a portable system to record acceleration data in biomechanics studies with precise time-stamping capabilities. The summary of this system development was presented in a peer-reviewed conference paper and a scientific peer reviewed journal paper, as described in Chapter 3 and 4.

Eight nurses and nursing students participated in the study and they wore five accelerometer sensors on their wrists, upper arms, and their backs. I used pattern recognition approach to discover patterns of six examples of nursing activities associated with accelerometer signals. In this approach, suitable features that represent the original phenomenon must be extracted from the signal under study. Feature extraction is critical in pattern recognition applications. Proper features makes it easier for classifiers to assign the signal to its belonging category. Therefore, the first step in automatically identifying the nursing activities recorded by accelerometer signals was to extract suitable features from the signal. I compared two popular features sets that previous researchers used to study human activities. The results of this study suggested that time domain features namely: mean, standard deviation, energy and correlation among accelerometers axes were suitable features to identify nursing activities recorded by accelerometers. These results were presented as a peer-reviewed conference paper as described in Chapter 3.
In another study that I explained in Chapter 4, I used the time domain features that were recommended in Chapter 3, and I evaluated the performance of three classifiers. The results showed that on average regardless of sensor location, up to 84% accuracy can be obtained if 1-NN classifier is used. However, I showed that accuracy dropped approximately by 20% when the classifier was trained on 10 trials and it was tested on the 11th that was a continuous trial of all combined examples of nursing activities. I showed that the best location for the sensor is on the back of a caregiver. For the Back sensor, the accuracy was highest for recognizing 'bed pan’ activity (91.96%) and the lowest for 'checking on vital signs' (74.2%).

Although the results obtain in Chapter 4 were promising, they were processed offline. This means that the data corresponding to the period of nursing activities were segmented, marking by a trained observer the start and stop time of each activity. A useful activity-based hand hygiene reminder system must be able to identify the onset of each activity in real-time. Therefore, in Chapter 5, I proposed a novel algorithm to achieve this. The proposed algorithm does not require any training. The algorithm was based on an RLS adaptive predictor filter. The algorithm identifies the onsets of the nursing activities when at least 2 of 3 axes showed significant changes in the acceleration signal not more than a second apart. The overall accuracy of the algorithm for a total of 96 events performed by the eight nurse subjects was 86.46% ± 12.55%. The accuracy was higher than 91% for 5 out of 8 subjects. The algorithm also indicated the onset of nursing sub-activities for a majority of the subjects. The results of this study, which have been published in a scientific peer-reviewed journal, suggest that the proposed algorithm may be useful in marking the transition points of human activities recorded by accelerometers.

Up to this point, I showed that it is possible to use accelerometers to recognize simple nursing activities that met the first objective of this research. These results may help to develop a nursing activity-based hand hygiene reminder system to remind caregivers cleanse their hands between dirty and clean sites (Moment 3 and Moment2 of WHO
model) on the patients. Once activities and hand hygiene opportunities are identified, the same information can be used to optimize the hand hygiene prompts in such reminder systems to save caregivers’ times allocated for hand washing. This could be achieved by including the risk of infection transfer into the logic of an intelligent hand hygiene reminder system before issuing a prompt.

As discussed in Chapter 6, I modified the WHO model of hand hygiene by associating different levels of risk to each moment as Low, Medium and High. I modelled the process by a discrete Markov Chain. Estimating the model transition matrix based on the recently published data, I was able to calculate the risk of infection transfer carried by the caregiver upon leaving the current patient. The results of the simulation showed that the high-risk of cross-contamination decreases exponentially by frequency of hand hygiene. I also found that if the caregiver enters the room with a high-risk of transferring infection to the current patient, given the assumptions in this study, only 55% hand hygiene compliance rate is capable of reducing the risk to the lowest level and helping to prevent the next patient from acquiring the infection. The model is also capable of simulating the effects of the imperfect hand hygiene on the risk of cross-contamination. This fulfils the second objective of this thesis. To my knowledge this is the first time such a model is proposed to study the risk of infection transfer based on WHO hand hygiene model. This work has been submitted and it is under review.

Although the tools and the algorithms that I developed and presented in this thesis were designed to identify nursing activities, such approaches can also be used in studying human activities recorded by accelerometer sensors.

### 7.2 Outstanding challenges

The studies conducted as part of this work were all proof of concepts and increasing the accuracy of the accelerometer-based nursing activity recognition system, described
in Chapter 4, was beyond the scope of this work. Therefore, there are limitations to this work. In order to implement the proposed work in a real-time hand hygiene reminder system, few technical and clinical considerations must be taken.

7.2.1 Technological consideration

Location information

Location awareness is challenging for accelerometer-based activity recognition systems. Such systems do not differentiate walking toward a patient in the patient zone from walking down the corridor with soiled/clean linen. Thus, including the location information is crucial to successfully classify real-time streams of activity-based acceleration data. Location information can be processed by means of infrared [49, 18, 107], ultrasound technology [108], radio frequency identification (RFID) [59], and environmental sound [109, 77], where a vision-based system can not be used. However, the cost of such systems may not be attractive to many healthcare settings.

Improving recognition accuracy

In the work presented in Chapter 4, I considered each nursing activity as a whole and the distinguishing features were extracted from the abstract of nursing activities. One way of improving the classification accuracy is to break down each nursing activity into its forming sub-component nursing activities. For example, placing a bedpan under the patient (assuming the bed pan is already on the bed, near the patient), requires the nurse to remove the patient’s blanket, roll the patient to the opposite side of the bed. While keeping the patient in this position with one hand, the nurse needs to place the bed pan under the patient with the other hand, roll back the patient, and finally cover the patient with the blanket. The algorithm that I presented in Chapter 5 is capable of marking the onset of each sub-activities.
Sequential classifiers such as Hidden Markov Models \[110\] may be trained on the sub-
activities and then discover the abstract activity. However, these models are useful as long
as the task orders are not randomly performed \[111\]. Instead, a hierarchical structure
may be used \[111\]. Another tool that has been shown to be successful in dealing with
dynamic behaviour change in simple human activities is Fuzzy Inference System due its
flexibility, and tolerance of imprecise data \[80\]. However, more research should be done
to validate the efficacy of such system in recognizing nursing activities.

Considering acceleration data from more than one sensor may help to increase the
accuracy of the system. Although in this work, as described in Chapter 4, the back sensor
showed acceptable accuracy in identifying nursing activities, its accuracy was not very
high in identifying 'check on the blood pressure' task (74.2\%). The Back sensor almost
equally confused 'check on the blood pressure' activity with the rest of the activities, due
to similarities among acceleration patterns sensed at the subject’s backs. Including the
data of the dominant hand or other sensors location into the feature space, may increase
the accuracy of the system and make it more robust in identifying nursing activities.

### 7.2.2 Clinical consideration

**Infection transfer risk factors**

In the model that I proposed in Chapter 6, the probability of transferring from lower
risk level into higher risk moment was dependant on many risk factors including type
of nursing activity, patient condition, frequency of the caregiving activities, efficacy of
hand hygiene and environmental factor. To my knowledge there is currently no study
available to show how to quantify these parameters. Therefore, proper scaling system
must be developed to study these factors. However, some of these risk factors may be
quantified with current tools and the contribution of each risk factor in the total risk may
be estimated using a Failure Mode and Effects Analysis (FEMA) risk analysis system.
For instance, the severity of the identified nursing activity may be estimated by Fulkerson scale [112] developed in 1971. This scale ranks the caregiving activities from the cleanest to the most contaminating. Feldman’s scale [112] has been used to audit the efficacy of hand washing using soap and water but to my knowledge there is currently no scale that scores the efficacy of hand hygiene using alcohol gels. Moreover, these rules may need to be revisited by infection control specialists (Fulkerson scale and Feldman’s score are shown in Appendix A and Appendix B respectively).

7.3 Future work

In this work I explored a portable technology to identify nursing activities, developed an algorithm to mark the onsets of nursing activities, and a model to optimize caregivers hand hygiene practises. Future work should include improving the accuracy of the system, explore more examples of nursing activities and when the technology is mature enough, it must be implemented in healthcare settings to study the long-term effects of such technology in promoting hand hygiene to fight HAI and consequently, increase patient safety, reduce mortalities, and costs associated with HAI.
Appendix A

Fulkerson Scale

<table>
<thead>
<tr>
<th>Rank</th>
<th>Contact with</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Sterile or autoclaved materials</td>
</tr>
<tr>
<td>2</td>
<td>Thoroughly cleaned or washed materials</td>
</tr>
<tr>
<td>3</td>
<td>Materials not necessarily cleaned but free from patient contact (e.g., papers)</td>
</tr>
<tr>
<td>4</td>
<td>Objects contacted by patients either infrequently or not expected to be contaminated (e.g., patient furniture)</td>
</tr>
<tr>
<td>5</td>
<td>Objects intimately associated with patients, but not known to be contaminated (e.g., patient gowns, linens, dishes, bedside rails)</td>
</tr>
<tr>
<td>6</td>
<td>Patient, but minimal and limited (e.g., shaking hands, taking pulse)</td>
</tr>
<tr>
<td>7</td>
<td>Objects in contact with patient secretions</td>
</tr>
<tr>
<td>8</td>
<td>Patient secretions or mouth, nose, genitoanal area, etc.</td>
</tr>
<tr>
<td>9</td>
<td>Materials contaminated by patient urine</td>
</tr>
<tr>
<td>10</td>
<td>Patient urine</td>
</tr>
<tr>
<td>11</td>
<td>Materials contaminated with feces</td>
</tr>
<tr>
<td>12</td>
<td>Feces</td>
</tr>
<tr>
<td>13</td>
<td>Materials contaminated with secretions or excretions from infected sites</td>
</tr>
<tr>
<td>14</td>
<td>Secretions or excretions from infected sites</td>
</tr>
<tr>
<td>15</td>
<td>Infected patient sites (e.g., wounds, tracheotomy)</td>
</tr>
</tbody>
</table>

1 “Clean” activities, 1-7; “dirty” activities, 8-15.
Appendix B

Feldman’s Hand-washing Criteria
<table>
<thead>
<tr>
<th>Action</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Used soap</td>
<td></td>
</tr>
<tr>
<td>Visible lather</td>
<td>2</td>
</tr>
<tr>
<td>No contact with soap</td>
<td>0</td>
</tr>
<tr>
<td>Used continuously running water</td>
<td></td>
</tr>
<tr>
<td>Did</td>
<td>2</td>
</tr>
<tr>
<td>Did not</td>
<td>0</td>
</tr>
<tr>
<td>Positioned hands to avoid contaminating arms</td>
<td></td>
</tr>
<tr>
<td>Held hands down so that water drained from fingertips into sink</td>
<td>2</td>
</tr>
<tr>
<td>Held hands parallel with arms so that water drained from hands into sink</td>
<td>1</td>
</tr>
<tr>
<td>Held hands up so that the water drained onto arms</td>
<td>0</td>
</tr>
<tr>
<td>Avoided splashing clothing or floor</td>
<td></td>
</tr>
<tr>
<td>No splashing</td>
<td>2</td>
</tr>
<tr>
<td>Minimal splashing</td>
<td>1</td>
</tr>
<tr>
<td>Vigorous splashing</td>
<td>0</td>
</tr>
<tr>
<td>Rub hands together vigorously</td>
<td></td>
</tr>
<tr>
<td>Vigorous rubbing</td>
<td>2</td>
</tr>
<tr>
<td>Minimal rubbing</td>
<td>1</td>
</tr>
<tr>
<td>No rubbing</td>
<td>0</td>
</tr>
<tr>
<td>Used friction on all surfaces</td>
<td></td>
</tr>
<tr>
<td>Dorsal, ventral and interdigital</td>
<td>2</td>
</tr>
<tr>
<td>One or two of the above</td>
<td>1</td>
</tr>
<tr>
<td>No friction</td>
<td>0</td>
</tr>
<tr>
<td>Rinsed hands thoroughly</td>
<td></td>
</tr>
<tr>
<td>All surfaces: dorsal, ventral, interdigital</td>
<td>2</td>
</tr>
<tr>
<td>One or two of the above</td>
<td>1</td>
</tr>
<tr>
<td>Did not rinse</td>
<td>0</td>
</tr>
<tr>
<td>Held hands down to rinse</td>
<td></td>
</tr>
<tr>
<td>Did</td>
<td>2</td>
</tr>
<tr>
<td>Did not</td>
<td>0</td>
</tr>
<tr>
<td>Dried hands thoroughly</td>
<td></td>
</tr>
<tr>
<td>Dried all surfaces</td>
<td>2</td>
</tr>
<tr>
<td>Dried one or two surfaces</td>
<td>1</td>
</tr>
<tr>
<td>Did not dry</td>
<td>0</td>
</tr>
<tr>
<td>Turned faucet off with paper towel</td>
<td></td>
</tr>
<tr>
<td>Did</td>
<td>2</td>
</tr>
<tr>
<td>Did not</td>
<td>0</td>
</tr>
<tr>
<td><strong>Maximum score</strong></td>
<td>20</td>
</tr>
</tbody>
</table>
Appendix C

Toronto Rehabilitation Institute
Research Ethics Approval
January 30th, 2009

Dr Geoff Fernie
Toronto Rehabilitation Institute
TRI - University Centre
550 University Avenue
Toronto, ON M5G 2A2

Dear Dr. Fernie:

RE: TRI REB # 08-040
Identifying Nursing Activities to Estimate the Risk of Cross-Contamination.

The Toronto Rehabilitation Institute Research Ethics Board has reviewed the above-named submission. Any concerns and requested revisions have been addressed to the satisfaction of the REB. The protocol (dated August 12, 2008) and the Study Participant Consent Form - Phase 1 (undated, received January 6, 2009) are approved for use for the next 12 months. If the study is expected to continue beyond the expiry date, you are responsible for ensuring the study receives re-approval. The REB must also be notified of the completion or termination of this study and a final report provided.

The following documents are also approved:

- Study Participant Information Form - Phase 1 - (undated, received January 6, 2009)
- Study Participant Information Form - Phase 2 - (Version 1.1, undated, received January 6, 2009)
- Study Participant Information Form - Phase 3 - (Version 1.1, undated, received January 6, 2009)
- Study Participant Consent Form - Phase 2 - (undated, received January 6, 2009)
- Study Participant Consent Form - Phase 3 - (undated, received January 6, 2009)
- Appendix A - Recruitment Email – (Version 1.1, received January 6, 2009)
- Telephone Screen - (undated, received January 6, 2009)
- Recruitment Poster - (undated, received January 6, 2009)
Page 2

TRI REB file# 08-040

Dr. Fernie

January 30th, 2009

If, during the course of the research, there are any serious adverse events, changes in the approved protocol or consent form or any new information that must be considered with respect to the study, these should be brought to the immediate attention of the Board.

Best wishes for the successful completion of your project.

Yours sincerely,

Gaétan Tardif MD FRCPC
Chair, Research Ethics Board
Toronto Rehabilitation Institute

January 30, 2009
Date of Initial REB Approval

January 30, 2010
Expiry Date of REB Approval
Appendix D

University of Toronto Research Ethics Approval
Dear Dr. Fernie and Mr. Momen:

Re: Administrative Approval of your research protocol entitled, “Identifying nursing to estimate the risk of cross-contamination”

We are writing to advise you that the Office of Research Ethics has granted administrative approval to the above-named research study. The level of approval is based on the following role(s) of the University, as you have identified with your submission:

- Graduate Student research – hospital-based only
- Storage or analysis of De-identified Personal Information (data)

This approval does not substitute for ethics approval, which has been obtained from your hospital Research Ethics Board. Please note that you do not need to submit Annual Renewals, Study Completion Reports or Amendments to the ORE unless the involvement of the University changes so that ethics review is required. Please contact the ORE to determine whether a particular change to the University’s involvement requires ethics review.

Best wishes for the successful completion of your project.

Yours sincerely,

Daniel Gyewu
Research Ethics Coordinator
Appendix E

1-Nearest Neighbour (1-NN) classifier performance on activity recognition for all sensors
### Appendix E. 1-NN classifier performance for all sensors

Table E.1: The Left Wrist sensor recognition rate; aggregated confusion matrix for 1-NN classifier tested on Dataset1, based on 10-fold cross-validation for 8 subjects.

<table>
<thead>
<tr>
<th>Predicted Activity</th>
<th>Actual Activity</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>a b c d e f</td>
<td>b = Place a Bed Pan</td>
<td>87.88</td>
</tr>
<tr>
<td>435 4 16 5 21 14</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 342 5 11 2 37</td>
<td>b = Place a Bed Pan</td>
<td>85.50</td>
</tr>
<tr>
<td>22 8 254 2 5 16</td>
<td>c = Give Oral Medication</td>
<td>82.74</td>
</tr>
<tr>
<td>4 10 7 418 4 17</td>
<td>d = Replace an IV Bag</td>
<td>90.87</td>
</tr>
<tr>
<td>16 2 4 2 382 18</td>
<td>e = Talk to the Patient</td>
<td>90.09</td>
</tr>
<tr>
<td>18 24 17 19 18 308</td>
<td>f = Check on Blood Pressure</td>
<td>76.24</td>
</tr>
</tbody>
</table>

Table E.2: The Right Wrist sensor recognition rate; aggregated confusion matrix for 1-NN classifier tested on Dataset1, based on 10-fold cross-validation for 8 subjects.

<table>
<thead>
<tr>
<th>Predicted Activity</th>
<th>Actual Activity</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>a b c d e f</td>
<td>a = Blood Sugar Test</td>
<td>86.03</td>
</tr>
<tr>
<td>431 11 19 3 16 21</td>
<td></td>
<td></td>
</tr>
<tr>
<td>11 339 7 2 4 46</td>
<td>b = Place a Bed Pan</td>
<td>82.89</td>
</tr>
<tr>
<td>20 8 254 7 13 12</td>
<td>c = Give Oral Medication</td>
<td>80.89</td>
</tr>
<tr>
<td>11 5 6 433 6 4</td>
<td>d = Replace an IV Bag</td>
<td>93.12</td>
</tr>
<tr>
<td>8 7 12 6 387 15</td>
<td>e = Talk to the Patient</td>
<td>88.97</td>
</tr>
<tr>
<td>29 43 9 5 13 317</td>
<td>f = Check on Blood Pressure</td>
<td>76.20</td>
</tr>
</tbody>
</table>

Table E.3: The Left Upper Arm sensor recognition rate; aggregated confusion matrix for 1-NN classifier tested on Dataset1, based on 10-fold cross-validation for 8 subjects.

<table>
<thead>
<tr>
<th>Predicted Activity</th>
<th>Actual Activity</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>a b c d e f</td>
<td>a = Blood Sugar Test</td>
<td>85.74</td>
</tr>
<tr>
<td>421 0 9 5 32 24</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 339 10 10 2 35</td>
<td>b = Place a Bed Pan</td>
<td>84.96</td>
</tr>
<tr>
<td>8 8 246 10 12 25</td>
<td>c = Give Oral Medication</td>
<td>79.61</td>
</tr>
<tr>
<td>11 11 14 383 8 27</td>
<td>d = Replace an IV Bag</td>
<td>84.36</td>
</tr>
<tr>
<td>25 1 5 3 371 11</td>
<td>e = Talk to the Patient</td>
<td>89.18</td>
</tr>
<tr>
<td>29 41 22 28 17 266</td>
<td>f = Check on Blood Pressure</td>
<td>66.00</td>
</tr>
</tbody>
</table>
### Appendix E. 1-NN classifier performance for all sensors

Table E.4: The Right Upper Arm sensor recognition rate; aggregated confusion matrix for 1-NN classifier tested on Dataset1, based on 10-fold cross-validation for 8 subjects.

<table>
<thead>
<tr>
<th>Predicted Activity</th>
<th>Actual Activity</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>a b c d e f</td>
<td>a= Blood Sugar Test</td>
<td>84.66</td>
</tr>
<tr>
<td>425 3 13 3 26 32</td>
<td>7 331 11 7 3 47</td>
<td>81.53</td>
</tr>
<tr>
<td>14 13 242 8 18 20</td>
<td>c= Give Oral Medication</td>
<td>76.83</td>
</tr>
<tr>
<td>8 6 7 422 8 15</td>
<td>d= Replace an IV Bag</td>
<td>90.56</td>
</tr>
<tr>
<td>20 3 14 11 370 11</td>
<td>e= Talk to the Patient</td>
<td>86.25</td>
</tr>
<tr>
<td>35 37 20 11 17 296</td>
<td>f= Check on Blood Pressure</td>
<td>71.15</td>
</tr>
</tbody>
</table>

Table E.5: The Back sensor recognition rate; aggregated confusion matrix for 1-NN classifier tested on Dataset1, based on 10-fold cross-validation for 8 subjects.

<table>
<thead>
<tr>
<th>Predicted Activity</th>
<th>Actual Activity</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>a b c d e f</td>
<td>a= Blood Sugar Test</td>
<td>86.00</td>
</tr>
<tr>
<td>424 6 27 2 12 22</td>
<td>6 366 11 0 1 14</td>
<td>91.96</td>
</tr>
<tr>
<td>14 9 259 1 14 16</td>
<td>c= Give Oral Medication</td>
<td>82.75</td>
</tr>
<tr>
<td>4 0 4 400 14 30</td>
<td>d= Replace an IV Bag</td>
<td>88.50</td>
</tr>
<tr>
<td>13 0 10 7 369 23</td>
<td>e= Talk to the Patient</td>
<td>87.44</td>
</tr>
<tr>
<td>18 21 22 22 22 302</td>
<td>f= Check on Blood Pressure</td>
<td>74.20</td>
</tr>
</tbody>
</table>
Appendix F

Naïve Bayes (NB) classifier performance on activity recognition for all sensors
Table F.1: The Left Wrist sensor recognition rate; aggregated confusion matrix for NB classifier tested on Dataset1, based on 10-fold cross-validation for 8 subjects.

<table>
<thead>
<tr>
<th>Predicted Activity</th>
<th>Actual Activity</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>a b c d e f</td>
<td>a= Blood Sugar Test</td>
<td>88.48</td>
</tr>
<tr>
<td>438 8 17 2 6 24</td>
<td>b= Place a Bed Pan</td>
<td>83.00</td>
</tr>
<tr>
<td>1 332 7 2 4 54</td>
<td>c= Give Oral Medication</td>
<td>79.15</td>
</tr>
<tr>
<td>35 9 243 5 3 12</td>
<td>d= Replace an IV Bag</td>
<td>83.91</td>
</tr>
<tr>
<td>7 15 9 386 4 39</td>
<td>e= Talk to the Patient</td>
<td>74.06</td>
</tr>
<tr>
<td>51 4 24 5 314 26</td>
<td>f= Check on Blood Pressure</td>
<td>69.80</td>
</tr>
<tr>
<td>30 44 16 18 14 282</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table F.2: The Right Wrist sensor recognition rate; aggregated confusion matrix for NB classifier tested on Dataset1, based on 10-fold cross-validation for 8 subjects.

<table>
<thead>
<tr>
<th>Predicted Activity</th>
<th>Actual Activity</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>a b c d e f</td>
<td>a= Blood Sugar Test</td>
<td>85.03</td>
</tr>
<tr>
<td>426 10 21 5 18 21</td>
<td>b= Place a Bed Pan</td>
<td>79.22</td>
</tr>
<tr>
<td>22 324 7 2 4 50</td>
<td>c= Give Oral Medication</td>
<td>79.94</td>
</tr>
<tr>
<td>22 7 251 10 10 14</td>
<td>d= Replace an IV Bag</td>
<td>89.68</td>
</tr>
<tr>
<td>12 10 13 417 6 7</td>
<td>e= Talk to the Patient</td>
<td>85.75</td>
</tr>
<tr>
<td>10 8 14 13 373 17</td>
<td>f= Check on Blood Pressure</td>
<td>67.79</td>
</tr>
<tr>
<td>50 56 15 4 9 282</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table F.3: The Left Upper Arm sensor recognition rate; aggregated confusion matrix for NB classifier tested on Dataset1, based on 10-fold cross-validation for 8 subjects.

<table>
<thead>
<tr>
<th>Predicted Activity</th>
<th>Actual Activity</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>a b c d e f</td>
<td>a= Blood Sugar Test</td>
<td>77.60</td>
</tr>
<tr>
<td>381 0 21 0 50 39</td>
<td>b= Place a Bed Pan</td>
<td>78.95</td>
</tr>
<tr>
<td>2 315 16 14 0 52</td>
<td>c= Give Oral Medication</td>
<td>74.11</td>
</tr>
<tr>
<td>24 12 229 7 12 25</td>
<td>d= Replace an IV Bag</td>
<td>76.65</td>
</tr>
<tr>
<td>12 20 28 348 11 35</td>
<td>e= Talk to the Patient</td>
<td>89.42</td>
</tr>
<tr>
<td>23 1 12 1 372 7</td>
<td>f= Check on Blood Pressure</td>
<td>66.75</td>
</tr>
<tr>
<td>40 35 27 2 30 269</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table F.4: The Right Upper Arm sensor recognition rate; aggregated confusion matrix for NB classifier tested on Dataset1, based on 10-fold cross-validation for 8 subjects.

<table>
<thead>
<tr>
<th>Predicted Activity</th>
<th>Actual Activity</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>a  b  c  d  e  f</td>
<td>a= Blood Sugar Test</td>
<td>80.08</td>
</tr>
<tr>
<td>402  10  15  1  30  44</td>
<td>b= Place a Bed Pan</td>
<td>80.54</td>
</tr>
<tr>
<td>1  327  17  5  0  56</td>
<td>c= Give Oral Medication</td>
<td>78.10</td>
</tr>
<tr>
<td>16  11  246  11  12  19</td>
<td>d= Replace an IV Bag</td>
<td>80.90</td>
</tr>
<tr>
<td>11  13  24  377  12  29</td>
<td>e=Talk to the Patient</td>
<td>88.34</td>
</tr>
<tr>
<td>14  5  18  3  379  10</td>
<td>f=Check on Blood Pressure</td>
<td>59.86</td>
</tr>
</tbody>
</table>

Table F.5: The Back sensor recognition rate; aggregated confusion matrix for NB classifier tested on Dataset1, based on 10-fold cross-validation for 8 subjects.

<table>
<thead>
<tr>
<th>Predicted Activity</th>
<th>Actual Activity</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>a  b  c  d  e  f</td>
<td>a= Blood Sugar Test</td>
<td>82.76</td>
</tr>
<tr>
<td>408  8  31  2  6  38</td>
<td>b= Place a Bed Pan</td>
<td>88.44</td>
</tr>
<tr>
<td>6  352  19  0  0  21</td>
<td>c= Give Oral Medication</td>
<td>77.64</td>
</tr>
<tr>
<td>24  15  243  2  9  20</td>
<td>d= Replace an IV Bag</td>
<td>87.61</td>
</tr>
<tr>
<td>5  0  3  396  13  35</td>
<td>e=Talk to the Patient</td>
<td>86.97</td>
</tr>
<tr>
<td>12  0  10  15  367  18</td>
<td>f=Check on Blood Pressure</td>
<td>57.49</td>
</tr>
</tbody>
</table>
Appendix G

Decision Table (DT-J48) classifier performance on activity recognition for all sensors
Table G.1: The Left Wrist sensor recognition rate; aggregated confusion matrix for DT (J48) classifier tested on Dataset1, based on 10-fold cross-validation for 8 subjects.

<table>
<thead>
<tr>
<th>Predicted Activity</th>
<th>Actual Activity</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>a  b  c  d  e  f</td>
<td>a= Blood Sugar Test</td>
<td>83.64</td>
</tr>
<tr>
<td>414 7 23 4 24 23</td>
<td>b= Place a Bed Pan</td>
<td>75.50</td>
</tr>
<tr>
<td>6 302 7 18 15 52</td>
<td>c= Give Oral Medication</td>
<td>77.20</td>
</tr>
<tr>
<td>23 13 237 9 6 19</td>
<td>d= Replace an IV Bag</td>
<td>83.70</td>
</tr>
<tr>
<td>12 16 12 385 9 26</td>
<td>e= Talk to the Patient</td>
<td>83.73</td>
</tr>
<tr>
<td>26 7 5 4 355 27</td>
<td>f= Check on Blood Pressure</td>
<td>70.30</td>
</tr>
</tbody>
</table>

Table G.2: The Right Wrist sensor recognition rate; aggregated confusion matrix for DT (J48) classifier tested on Dataset1, based on 10-fold cross-validation for 8 subjects.

<table>
<thead>
<tr>
<th>Predicted Activity</th>
<th>Actual Activity</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>a  b  c  d  e  f</td>
<td>a= Blood Sugar Test</td>
<td>79.64</td>
</tr>
<tr>
<td>399 18 23 12 17 32</td>
<td>b= Place a Bed Pan</td>
<td>73.35</td>
</tr>
<tr>
<td>24 300 4 8 13 60</td>
<td>c= Give Oral Medication</td>
<td>76.11</td>
</tr>
<tr>
<td>19 10 239 9 15 22</td>
<td>d= Replace an IV Bag</td>
<td>87.74</td>
</tr>
<tr>
<td>17 12 11 408 3 14</td>
<td>e= Talk to the Patient</td>
<td>85.29</td>
</tr>
<tr>
<td>16 8 14 9 371 17</td>
<td>f= Check on Blood Pressure</td>
<td>68.75</td>
</tr>
</tbody>
</table>

Table G.3: The Left Upper Arm sensor recognition rate; aggregated confusion matrix for DT (J48) classifier tested on Dataset1, based on 10-fold cross-validation for 8 subjects.

<table>
<thead>
<tr>
<th>Predicted Activity</th>
<th>Actual Activity</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>a  b  c  d  e  f</td>
<td>a= Blood Sugar Test</td>
<td>81.67</td>
</tr>
<tr>
<td>401 6 12 5 38 29</td>
<td>b= Place a Bed Pan</td>
<td>81.45</td>
</tr>
<tr>
<td>4 325 13 17 2 38</td>
<td>c= Give Oral Medication</td>
<td>73.14</td>
</tr>
<tr>
<td>15 8 226 18 11 31</td>
<td>d= Replace an IV Bag</td>
<td>79.96</td>
</tr>
<tr>
<td>9 23 25 363 1 33</td>
<td>e= Talk to the Patient</td>
<td>83.89</td>
</tr>
<tr>
<td>34 2 11 6 349 14</td>
<td>f= Check on Blood Pressure</td>
<td>66.50</td>
</tr>
</tbody>
</table>
### Appendix G. Decision Table classifier performance for all sensors

Table G.4: The Right Upper Arm sensor recognition rate; aggregated confusion matrix for DT (J48) classifier tested on Dataset1, based on 10-fold cross-validation for 8 subjects.

<table>
<thead>
<tr>
<th>Predicted Activity</th>
<th>Actual Activity</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>a  b  c  d  e  f</td>
<td>a= Blood Sugar Test</td>
<td>79.68</td>
</tr>
<tr>
<td>400 11 21 9 23 38</td>
<td>b= Place a Bed Pan</td>
<td>77.34</td>
</tr>
<tr>
<td>7 314 16 19 7 43</td>
<td>c= Give Oral Medication</td>
<td>74.60</td>
</tr>
<tr>
<td>24 11 235 15 12 18</td>
<td>d= Replace an IV Bag</td>
<td>87.55</td>
</tr>
<tr>
<td>6 20 10 408 6 16</td>
<td>e= Talk to the Patient</td>
<td>80.65</td>
</tr>
<tr>
<td>31 3 19 12 346 18</td>
<td>f= Check on Blood Pressure</td>
<td>61.30</td>
</tr>
</tbody>
</table>

Table G.5: The Back sensor recognition rate; aggregated confusion matrix for DT (J48) classifier tested on Dataset1, based on 10-fold cross-validation for 8 subjects.

<table>
<thead>
<tr>
<th>Predicted Activity</th>
<th>Actual Activity</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>a  b  c  d  e  f</td>
<td>a= Blood Sugar Test</td>
<td>83.57</td>
</tr>
<tr>
<td>412 11 25 0 19 26</td>
<td>b= Place a Bed Pan</td>
<td>83.17</td>
</tr>
<tr>
<td>8 331 21 0 1 37</td>
<td>c= Give Oral Medication</td>
<td>76.36</td>
</tr>
<tr>
<td>31 13 239 4 11 15</td>
<td>d= Replace an IV Bag</td>
<td>88.05</td>
</tr>
<tr>
<td>4 2 3 398 16 29</td>
<td>e= Talk to the Patient</td>
<td>81.28</td>
</tr>
<tr>
<td>20 2 6 10 343 41</td>
<td>f= Check on Blood Pressure</td>
<td>65.11</td>
</tr>
<tr>
<td>24 31 22 32 33 265</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Bibliography


