ENHANCING THE HUMAN-TEAM AWARENESS OF A ROBOT

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Abstract

The use of autonomous robots in our society is increasing every day and a robot is no longer seen as a tool but as a team member. The robots are now working side by side with us and provide assistance during dangerous operations where humans otherwise are at risk. This development has in turn increased the need of robots with more human-awareness. Therefore, this master thesis aims at contributing to the enhancement of human-aware robotics. Specifically, we are investigating the possibilities of equipping autonomous robots with the capability of assessing and detecting activities in human teams. This capability could, for instance, be used in the robot's reasoning and planning components to create better plans that ultimately would result in improved human-robot teamwork performance. we propose to improve existing teamwork activity recognizers by adding intangible features, such as stress, motivation and focus, originating from human behavior models.

Hidden markov models have earlier been proven very efficient for activity recognition and have therefore been utilized in this work as a method for classification of behaviors.

In order for a robot to provide effective assistance to a human team it must not only consider spatio-temporal parameters for team members but also the psychological. To assess psychological parameters this master thesis suggests to use the body signals of team members. Body signals such as heart rate and skin conductance. Combined with the body signals we investigate the possibility of using System Dynamics models to interpret the current psychological states of the human team members, thus enhancing the human-awareness of a robot.

Sammanfattning

Användningen av autonoma robotar i vårt samhälle ökar varje dag och en robot ses inte längre som ett verktyg utan som en gruppmedlem. Robotarna arbetar nu sida vid sida med oss och ger oss stöd under farliga arbeten där människor annars är utsatta för risker. Denna utveckling har i sin tur ökat behovet av robotar med mer människo-medvetenhet. Därför är målet med detta examensarbete att bidra till en stärkt människo-medvetenhet hos robotar.

Specifikt undersöker vi möjligheterna att utrusta autonoma robotar med förmågan att bedöma och upptäcka olika beteenden hos mänskliga lag. Denna förmåga skulle till exempel kunna användas i robotens resonemang och planering för att ta beslut och i sin tur förbättra samarbetet mellan människa och robot. Vi föreslår att förbättra befintliga aktivitetsidentifierare genom att tillföra förmågan att tolka immateriella beteenden hos människan, såsom stress, motivation och fokus.

Att kunna urskilja lagaktiviteter inom ett mänskligt lag är grundläggande för en robot som ska vara till stöd för laget. Dolda markovmodeller har tidigare visat sig vara mycket effektiva för just aktivitetsidentifiering och har därför använts i detta arbete.

För att en robot ska kunna ha möjlighet att ge ett effektivt stöd till ett mänskligt lag måste den inte bara ta hänsyn till rumsliga parametrar hos lagmedlemmarna utan även de psykologiska. För att tyda psykologiska parametrar hos människor förespråkar denna masteravhandling utnyttjandet av mänskliga kroppssignaler. Signaler så som hjärtfrekvens och hudkonduktans. Kombinerat med kroppens signalerar påvisar vi möjligheten att använda systemdynamiksmodeller för att tolka immateriella beteenden, vilket i sin tur kan stärka människo-medvetenheten hos en robot.

Contents

1 Introduction

In recent years there has been a shift towards using robots in operations that are considered too dangerous or even physically impossible for humans to complete. For instance, in the oil disaster in the Gulf of Mexico in 2010, underwater robots were used to assess and finally stop the oil leak at a depth of nearly 1500 meters [37]. Many of today's robots are remotely controlled and are therefore relatively expensive to operate due to the cost of training operators as well as paying their salaries. Furthermore, when robots are used in situations such as military operations that are considered stressful, the human operator may act too slowly, or even worse irrationally, which would reduce robot's effectiveness [50, 18]. Hence, a lot of research has been conducted towards creating autonomous robots that can perceive and act in the environment by itself [29, 38].

To achieve a more human-aware robot, knowledge from several research fields is required. Some of these fields are for example:

- **Artificial Intelligence** (AI), contributing with machine learning algorithms and pattern classification methods [61].
- **System Dynamics** (SD), contributing with models of human behavior explaining the dynamics between physical and physilogical features [49, 48, 52].
- **Wireless Body Area Network** (WBAN), contributing with sensor technology for reading body signals without mobility constraints [73].
- **Psychology**, contributing with knowledge about the human mind and its behaviors [64].
- **Human-Robot-Interaction** (HRI), contributing with interaction models between robots and humans [22].

In order for a robot to extensively assist a human team it must first understand the behaviors of the team. This implies that the robot must not only understand team dynamics but must also be able to interpret the individuals within the team. Human constellations are complex and the existing representations of human-robot teamwork are insufficient [65]. To realize robots which can provide effective assistance in a human team a better understanding of human-robot teamwork is crucial. The fact that it requires a great amount of expertise from different domains makes it hard to achieve a robot with total human-awareness. However, the research has advanced through a synergy of several research areas in the recent years proving that robots will be able to assist human teams more extensively in a near future.

An essential part of a sufficient human-robot teamwork model is the robot's capability of recognizing teamwork behavior. The existing teamwork activity recognizers [45, 46, 75] typically take into consideration spatio-temporal features such as relative position and orientation over time, they do not, however incorporate features describing the inherently fuzzy concepts of human behavior.

To assess the behaviors and activities of a human team we assume that the team changes its behavior according to the change of the situation around it. Thus, when a situation changes it will most certainly affect the members of the team physically, physiologically and psychologically. With the help of sensors we can observe physiological and physical changes such as position, orientation, heart rate and skin conductance of team members. To observe psychological changes a more sophisticated method must be applied. By utilizing these signals in a psychological model we can estimate the current state of team members and better classify team behavior [6].

In this thesis we are focusing on how autonomous robots can be integrated in human teams. Specifically, we are investigating the possibilities of equipping autonomous robots with the capability of assessing and detecting activities in human teams. This capability could, for instance, be used in the robot's reasoning and planning components to create better plans that ultimately would result in improved human-robot teamwork performance. we propose to improve existing teamwork activity recognizers by adding intangible features, such as motivation, satisfaction and stress, originating from human behavior models.

The thesis work has contained a wide variate of challenges. Research of how the human body can be interpreted have been conducted parallel to the development of the proposed and extended recognizer system. A validation process was designed and applied to prove the advantage of the proposed system. A data acquisition program was also built and used to produce artificial datasets for the validation. The feature extraction process in the data acquisition program is using a SD model to interpret body signals in order to extract the vague physiological behaviors of the human team members. The actual recognizer is based on hidden markov models (HMM). HMMs have been proven very efficient for activity recognition [47, 30] and are often used in the field of probability theory. More about the fundamentals of HMMs can be found in Appendix A.

The purpose of the extended recognizer system is to be utilized in order to enhance the human awareness of robots.

The thesis also discuss related subjects that are relevant for enhancing the human-team awareness of a robot, such as existing representation models of human behaviors, classification methods, sensor systems for reading body signals and how these signals can be utilized.

1.1 Problem statements

- **Integration of a human-team oriented robot**

  The long term goal for this thesis is to enable the use of robots in human teams. For this to be possible it is a requirement for a robot to have the ability to interpret individuals in a team. Only then can a robot have the possibility to fully understand the behaviors and dynamics in a human team.

- **Interpretation of intangible behaviors of a human team**

  This thesis aims to solve a problem that arise when integrating autonomous robots into human teams. Namely the interpretation of intangible behaviors of human teams and individuals, which is a problem that can manifest itself in different ways. There are numerous human behaviors that are of interest for the human awareness of a robot, even behaviors that are difficult to assess only by looking at spatial-temporal data. Behaviors such as confusion, motivation, stress and focus to mention a few.

- **Datasets for validation**

  The method chosen to solve the problem stated first requires a validation to prove its reliability and importance. This validation in turn give raise to the problem of finding suitable datasets for the validation.

1.2 Challenges

Some of the major challenges that are addressed in this thesis are listed below.

- **Synergy of research domains is required**

  It is very challenging to equip a robot with the ability to understand intangible behaviors since it requires a synergy of knowledge from different research domains. The problem solving involves everything from medical domains, such as psychology and physiology, to technical domains, such as sensor networks and machine learning.

- **Development of an adequate SD model**

  To solve the classification of intangible behaviors of humans and human teams we utilize a SD model. There is a great lack of detailed and presented SD models of human behaviors which makes it hard to establish an adequate model. Most of the existing models are merely concepts of human intangible behaviors and have no implementation. In this thesis, as much knowledge as possible about the human physiology and psychology have been retrieved in order to estimate the interdependencies of the developed SD model.

- **Creation of suitable datasets for validation**

  Suitable datasets are essential in order to validate and emphasize the importance of the SD model. The specific dataset originates from a specific scenario which must include all necessary agent features and team behaviors to be useful as a validation dataset. Thus, the scenario can point out which applications and scenarios the proposed method can be useful in.

1.3 Applications

Potential applications for a robot equipped with the proposed system are listed below.

- **Search and rescue operations**
- **Military operations**
- **Police operations**
- **Firefighting operations**
- **Space operations**

1.4 Tools

In this thesis work we have utilized several tools to accomplish the goal. They are all free for educational use and are listed below.

- **Eclipse RCP** - Eclipe is a multi-language software development environment and provides a platform for the development of general applications. It is called the Rich Client Platform (RCP) and was used to build a data acquisition program in this thesis.
- **JaHMM** - JaHMM is a Java framework for hidden markov models. It provides the necessary tools for building and customizing own models. It also provides various algorithms that can be used on models. Algorithms such as Forward-Backward, Viterbi, Baum-Welch and K-Means among others.
- **RapidMiner** - RapidMiner is a Java-based open-source data mining and machine learning software program. It has a Graphical User Interface (GUI) where the user works with blocks of various functionalities and links out- and inputs. RapidMiner provides a wide variety of functionalities which the operator blocks can have. A linked pipeline of operator blocks is called operator tree. The operator tree is in turn generated in to an XML (eXtensible Markup Language) file which defines the processes that the user wants to apply to a dataset. RapidMiner can present results of processed data in terms of matrices and graphs. The functionalities in RapidMiner can be extended with additional plug-ins. A plug-in based on JaHMM for HMM learning developed at FOI was utilized in this thesis work. More about the specific plug-in and how it is used is described in Section 6.2.4.
- **Vensim** - Vensim is a software tool for creating SD models developed by Ventana System, Inc. The software was used for developing SD models of human behavior.

1.5 System overview

This section describes the high-level design of the validation process of the developed system. It consists of five sections which together create, refine, assemble, utilize and analyze data. The process is shown in Figure 1.

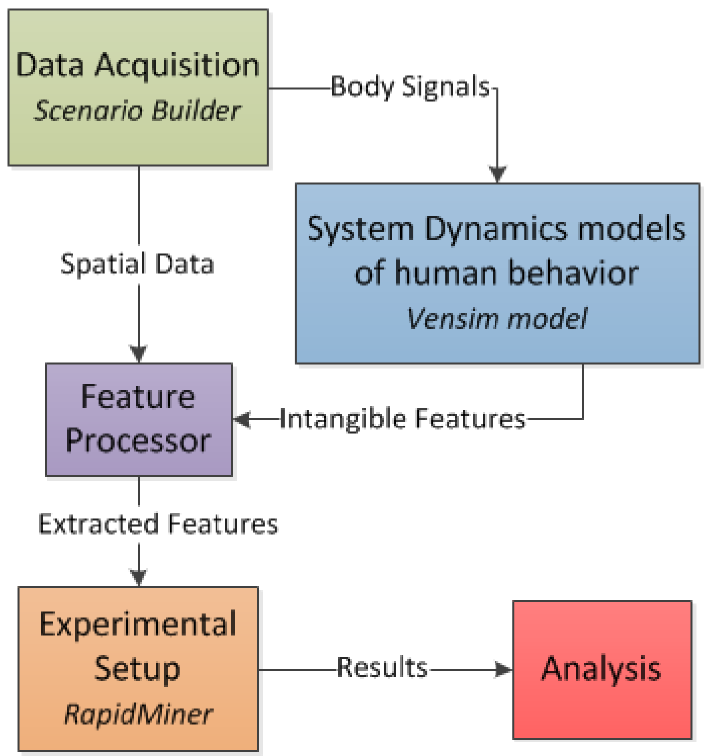

Figure 1: High-level design of the validation process of the system.

- **The green block** represents the data acquisition tool called Scenario Builder. It was developed in order to create datasets for custom scenarios which in turn was used to test and validate the system.

- **The purple block** is the feature processor. It is in fact a part of the data acquisition tool but is very important and is therefore placed outside the green block for clarity. The feature processor is the system element which assemble raw data into datasets.

- **The blue block** extend the feature processor with the ability to include intangible features in the datasets. The block receives raw data from Scenario Builder which is inserted in a SD model. The model in turn generates new features which are acquired by the feature processor.

- **The orange block** represents a more comprehensive subprocess of an experimental setup for testing the developed recognizer. Generally, it utilizes the extracted features i.e. the dataset from the feature processor to train HMMs. The extracted dataset contains a large amount of features also known as attributes. Since it is non-optimal to use all features [33] for classification the subprocess selects which features to train the HMMs with. To assess the classification performance of the recognizer the subprocess executes a 10 fold cross-validation of the recognizer. In order to have the possibility to compare the developed recognizer with existing recognizers the same validation procedure was applied on the system without the extension of the blue block.

- **The red block** illustrates the analysis stage of the process. The results from the orange block are compared and evaluated in order draw conclusions and prove the advantage of the extended recognizer.

1.6 Contributions

This section presents the contributions this thesis has produced.

1.6.1 System Dynamics integrated human activity recognizer

A system dynamics extended recognizer with the proven ability to better assess intangible activities of human teams. It is the system dynamics model that improves the capability of the recognizer by refining raw data into intangible features which can be utilized. The recognizer increases the possibilities of enhancing the human-awareness of robotic agents. Thus, this contribution addresses the second challenge in Section 1.2.

1.6.2 Data acquisition tool - Scenario Builder

A Java based program for creation of custom scenarios with the ability to extract datasets. It is a flexible and expandable data acquisition tool which allows the user to compose scenarios of any kind. It enables the possibility to extend and improve a dataset bit by bit until it is adequate. The user defines everything from world context to agent features and behaviors. Thus, this contribution manage the third challenge in Section 1.2. The tool has the functionality to utilize SD models in order to generate new feature data. The export option in the program is customizable, making it possible to customize the dataset in terms of included features and sample rate. The program also supports save and load option of scenarios.

1.6.3 A concept of human-robot interpretation

A comprehensive literature study in the fields of HRI and WBAN has led to the development of a human-robot interpretation concept. This thesis advocates that humans in a human-robot team utilize WBANs to provide the robot with essential body data. Combined with the proposed activity recognizer the signals obtained by a WBAN can be used to enhance the human awareness of a robot. Thus, this contribution suggests how the first challenge in Section 1.2 can be managed.

1.7 Outline

The remainder of this thesis is organized as follows.

Chapter 2: Related work
Chapter 2 reviews related research. It gives a brief background on existing human-robot teamwork models. Other essential areas are studied and their specific importances are discussed.

Chapter 3: Human-Robot concept
Chapter 3 briefly introduces the proposed concept of how to provide a robot with essential data from the human body in order to utilize it.

Chapter 4: Data acquisition and feature processing
In Chapter 4 describes the creation of artificial datasets with data acquired from Scenario Builder. The feature processor which assemble the dataset is explained.

Chapter 5: Extending the feature processor with features of human behavior
Chapter 5 introduces human-factor modeling with System Dynamics and the development of a model is discussed. The chapter also describes how intangible features are generated by the model.

Chapter 6: System test and experimental results
In Chapter 6 an experimental setup is used to test and validate the developed system. The outcome is discussed and evaluated.

Chapter 7: Conclusions
Finally in Chapter 7 conclusions of the thesis work is presented and future work is discussed.

2 Related work

2.1 Human-Robot teams

Humans have worked as a team for as long as we have known. It is a way of enhancing our capabilities. We have learned that we can accomplish more by working together.

Humans have also discovered that tools and machines can be used in order to increase efficiency or even to enable execution of certain tasks. The machines can be seen as a team member aiding the team and in some cases even replace a human team member. With the declining costs and increased availability of robotic agents the use of robots will increase. A robot in a human team will act more as a team member rather than a tool.

This section briefly discuss human-robot teaming which refers to the collaboration between humans and robotic agents [40]. Today we have both autonomous and remotely operated robots that aid human teams.

The main reason for having a robot in a human team is to extend the capabilities of the team. A robot may be able to perform tasks that are unsuitable or even impossible for a human. This leads us to another important reason, the fact that a robot can replace a human in situations where the human otherwise would be exposed to danger. Due to our human limitations such as vulnerability, oxygen requirement or body structure many tasks are impossible for us to solve. A robot on the other hand can be designed for a specific task. Hence, future teams consisting of both humans and robots have more potential in means of performing tasks efficiently and safely.

Integrating robots into human teams is challenging in many aspects. The team members, both humans and robots must understand each other and be aware of the situation of the team. Situation awareness (SA) is a key research [41, 14, 8] in the field of HRI. Researchers suggests that shared mental models (SMM) should be used to achieve a sufficient situation awareness [9, 20]. SMMs are measurable models developed among team members prior to task execution and are correlated to team performance [55]. It is an approach to predict needs and coordinate the behaviors of the team.

The ability to recognize, classify and predict human behavior is another important part of a team-working robot's AI. Research [30, 39, 1, 62] emphasizes the importance for a team working robot to understand human behavior. By possessing such ability a robot will be more human-aware. In [53] a human-aware framework is presented and discussed. The framework monitors user state, both physical and psychological in order to achieve an extensive human-context-awareness.

2.1.1 Real-world applications

In hazardous environments where humans are exposed to danger it is preferable to replace them with a robotic agent. Space exploration takes place in such hazardous environment. NASA and General Motors have developed a humanoid robot called robonaut stationed at the International Space Station [17]. It is a robot designed to work with humans in space. It has the ability to use the same tools as the human astronauts which makes it a good robotic astronaut to solve problems with.

Human-robot teams have been used and explored extensively in search and rescue operations [27, 31]. In urban search and rescue operations the specific objective is to rescue victims from collapsed man-made structures. It is clearly dangerous to have humans searching for survivors in collapsed and unstable buildings. This suggests that Human-Robot teams are suitable in search and rescue operations. Search and rescue exercises have shown that a human-robot team with an effective SMM are nine times more likely to find victims [9]. During the aftermath of the World Trade Center disaster small mobile robots collaborated with humans in order to locate and rescue victims [10]. The rescue operations revealed that both humans and robots contributes with unique qualities to the team. Robots are able to go in to difficult environments and spaces deemed too small or dangerous for humans or dogs. Human team members contribute with SMMs which enhance the situational awareness which in turn provide effective search and rescue.

Military environment is also hazardous for humans and there has been extensive research in the field of HRI for military purpose [2, 35]. Military forces have always used high tech machinery in order to lower the rates of causalities in field. The usage of robots in warfare is yet another try to reduce those numbers of causalities. In todays warfare robots have multiple purposes and objectives such as decision support, espionage, surveillance, locate mines and detonate them and so on. Robots are used in all three main forces; Army, Navy and Air.

Robots have also been proven useful in the hospital domain. Robotic agents in hospitals can contribute with routine delivery of medicine to patients and transport medical devices within the hospital [24, 68]. This relieves hospital personnel allowing them to pay more attention to the patients and focus on treatment.

2.2 Teamwork and multi-agent activity recognition

Teamwork activity recognition is crucial for the intelligence of a team-working robot. In order to interpret and understand the team the robot must recognize occurrence of team behaviors. Team activity encompasses several different sub-activities such as movement, formation, gestures-communication and speech-communication. Sub-activities in turn have different patterns that will appear and reveal the on going activity. It is possible to classify some of the activities in the team by focusing on one or more of these sub-activities. To fully interpret a team it would be necessary to capture all of the sub-activities.

An essential part of activity recognition is pattern classification. It contributes with pattern matching algorithms which search for matches in the input with pre-existing patterns. In teamwork activity recognition it is used to identify and classify team activities. Each known activity has its correlated pattern modeled in some way.

Existing teamwork activity recognizers are focusing on movement classification [45, 46, 75]. It takes into consideration spatio-temporal features such as relative position and orientation over time. In [46] HMMs are used in order to represent team activities which in this particular case correlates to patterns of spatio-temporal features. Experiments have validated that HMMs have good recognition accuracy.

Other activity recognizers that focus on activity classification rather than teamwork activity classification have classified human daily activities [82, 3]. Video and motion data is used in order to identify the different activities. Gesture classification research has specifically been conducted to enhance HRI [43].

2.3 System Dynamics

System Dynamics originates from research in business and economics [23]. Basically it is a way to model the behavior of complex dynamic systems over time. It do so by breaking down a complex system into separate parameters that is interconnected within the system. SD models represent the systems through feedback loops and time delays which brings forth the characteristics of the system.

System dynamics is suitable for any complex system that change over time and have therefore many fields of application. It is an established and useful simulation approach and it has the ability to predict how a system will react and evolve due to changes in the system. More about the fundamentals of system dynamics can be found in Appendix B.

System dynamics has been applied in several research projects to address specific problems of the development of urban areas [72, 66]. Urban development is composed of many variables which makes system dynamics a suitable modeling approach. Created SD models can be used to simulate the interaction between transport, population, resources and economic activity etc. in an urban environment.

In [12] a systems dynamics approach was used to model the flow and circulation of material, energy and information in an eco-city which is a city coordinated with three aspects; economy, society and nature. The purpose of the model was to simulate different scenarios of the city development. The system dynamics software Vensim PLE was used to emphasize the most optimal scenario.

More interesting for this thesis work is the research of modeling human behavior with system dynamics. It is a wide research area with many science domains involved. The SD model MODERE (Motivation, DEsire, REality) [25] describes parts of the dynamics of human behavior and motivation. It is based on theories of human behavior originating from social science proven helpful in analysis of human motivation and corresponding behavior. The model attempts to explain what induces individuals and groups to act in response to changes. The model was further developed and implemented as a tool in [48]. The MODERE-model is addressed more in Section 5.

Good human-factor modeling is difficult to achieve but is essential for a robot in a human team. Human-factor models can be used to enhance the human awareness of a robot [52]. It allows robots to mimic human behavior in order to achieve more human-like AI. SD models provide a better understanding and a chance to interpret the fuzzy behaviors of a human individual or group.

Human-robot teams are most used or intended to be used for tasks that are dangerous and stressful. Therefore, It is important for robotic agents to have the ability to understand human stress response. Psychiatric research have applied a system dynamics approach in order to understand the correlation between cortisol reactivity and stress disorders [49]. The result have shown that the proposed model has a powerful predicting potential in clinical practice. Besides, medical research has also revealed that certain transitions of breathing patterns over time may have high co-occurrence with stress levels of patients [71]. Knowledge discovery was conducted in [78] to identify key sequences of patterns for classification of stress levels.

2.4 Interpretation of human behavior

Human behavior express itself physically , physiologically and psychologically. They are however connected and it is essential to take into account all three when interpreting human behaviors. For instance when humans are stressed psychologically the body reacts by releasing hormones that physiologically affects the organs which in turn affect the physical ability. Research in all three areas have contributed to a better understanding of human behavior.

Much research has been dedicated to find different approaches for interpreting various human activities. It has contributed with a wide variety of approaches, such as capturing human emotion patterns that is connected to human inner states (motivations, drives and personalities) [21] to approaches for interpretation of physical behaviors such as gestural communication [70, 56].

Both physical and physiologic activity can be interpreted with the help of sensors. Especially for humans that are on the move a WBAN is suitable for data collection. The fundamentals of WBAN is presented and discussed more in Section 2.5.

As mentioned throughout the thesis, stress detection is essential for interpretation of human behavior. Human stress is a state that occur when a person respond to the demands and pressures that arise from a situation. It can have both positive and negative impact on a human. Thus, it reveals a lot about the human status and the current situation which can be used to enhance situation awareness in robotic agents. Former approaches for solving the stress detection problem have been based on physiological signals or behavioral characteristics.

2.4.1 Stress detection by means of physiological signals

When developing stress detection by means of physiological signals it is important to know which signals that can be related to stress. Signals that have been utilized in former research are presented in Table 1. More than one of these signals are often used in order to obtain a better understanding of the state of mind and in turn achieve accurate and precise stress detection.

Physiological signals	Abbreviation	Reference
Heart Rate	HR	[11, 16, 57, 76]
Heart Rate Variability	HRV	[59, 26, 74]
Galvanic Skin Response	GSR	[16, 58, 80, 81, 57, 59, 60]
Skin Temperature	ST	[80, 79]
Finger Temperature	FT	[5, 4, 19]
Pupil Diameter	PD	[80, 81, 60]
Blood Volume Pressure	BVP	[80, 59, 60]
R wave to R wave interval	RR	[57, 59]
Electrocardiogram	ECG	[57, 59]
Electromyogram	EMG	[59, 60]
Electroencephalogram	EEG	[59]

Table 1: Former research by means of physiological signals

A stress detection system can be used in a variety of applications. For example, the work presented in [15] utilizes physiological signals for stress detection to enhance the performance of biometric security systems. The signals that was used and provided a precise stress detection was galvanic skin response (GSR) and heart rate (HR). The work is real-time orientated which often leads to a reduction in stress detection accuracy. However, a real-time stress detection is necessary in many applications. In [16] HR and GSR signals was utilized and achieved a real-time stress detection rate of 99,5% in a study of 80 subjects.

2.4.2 Stress detection by means of behavioral characteristics

When recording behavioral characteristics for stress detection the most common approach is to use a video stream. It is important to note that this are behaviors that a human can control and manipulate. However, a stressful situation will affect the behaviors to a certain extent. Table 2 presents a couple of behavioral characteristics that have been observed and utilized in former research.

Behavioral and physical signals	Reference
Movement	[63, 44]
Eye Gaze	[60, 44]
Facial Expression	[44]

Table 2: Former research by means of behavioral characteristics

2.5 Wireless Body Area Network

In recent years patient monitoring has gained much interest in the field of health care. This have triggered extensive research and development of wireless sensor systems with the purpose of monitoring the human body and its environment [73].

Recent advances in electronics and sensor technology have enabled the development of tiny biomedical sensors which can be implanted in the body or deployed on the outside. Previous approaches have used a wired solution between sensors and a data acquisition unit. It has proven to be a less optimal solution in terms of deployment and maintenance costs. Therefore, a wireless approach is suitable and have lead to the development of WBAN [42, 13].

WBAN is a radio frequency based network of various sensors and in some applications actuators that is attached on, in or around the body. The sensors measure certain physiological or physical parameters of the human body such as heart activity [36], skin temperature [7], body movements [34] and skin conductance [7]. Actuators can utilize acquired sensor data and act accordingly in order to interact with the human body. All the sensors and actuators are connected to a common gateway unit also called personal server that for instance can be a smart phone or a Personal Digital Assistant (PDA). The personal server can analyze data, control actuators and transmit essential data wireless to an antenna for broadcasting or to an external server for further processing.

2.5.1 Applications

Patient monitoring

WBANs are already in use at health service facilities and are helpful by providing a better health care. It allows continuous monitoring of a humans physiological signals. This allows physicians to observe a patient and detect abnormalities. A WBAN equipped with actuators such as injectors for injecting life-saving drugs can be used by diabetics for example. There are several application field tests [5] where WBANs and medical record servers have been used for medical diagnosis.

Safeguarding of uniformed personnel

Uniformed personnel are often exposed to great risks and stressful situations. To lower the risks a WBAN can be used to read physiological signals that can indicate stress levels [58]. A network equipped with gas sensors can be used to detect and read levels of toxics in the air. This way the WBAN user can be aware of the risks.

physical rehabilitation

By utilizing a WBAN equipped with motion sensors it is possible to achieve a better physical rehabilitation at lower cost. In [28] a WBAN approach was used to detect and classify limb activities in an arm rehabilitation scenario.

Training professional athletes

In [54] WBAN is used to provide coaches and their athletes with training data which they can analyze. By looking at recorded data it is possible to follow and control the development of the athlete and ultimately enhance his or her performance. Another research [69] implements a WBAN to enhance the performance of rowing athletes.

3 Human-Robot concept

This chapter briefly describes the proposed concept of human-robot interpretation.

It is crucial for any team that all team members have a good understanding of the current state of the team and its individuals. This applies even if a team member is an autonomous robot. A sufficient amount of information and the ability to interpret it is a requirement in order to have a good understanding.Teams consisting of only humans are often attuned due to knowledge in terms of previous experience. This leads to much higher task performance and indicates that a robot also must have experience and knowledge. With experience it is possible for a robot to utilize acquired data to interpret the human team members and achieve a better understanding [51]. Thus, a first step of achieving a good human understanding is to acquire the essential data.

A WBAN is suitable for collecting signals emitted from the human body as described in Section 2.5. Data can easily be distributed with a WBAN which makes it possible to connect team members to a robot as this thesis suggest. Another benefit with a WBAN is the fact that it does not limit the mobility of the user.

To interpret the acquired data a recognizer of human behavior can be utilized. Such as the recognizer proposed in this thesis. Figure 2 illustrates the concept structure.

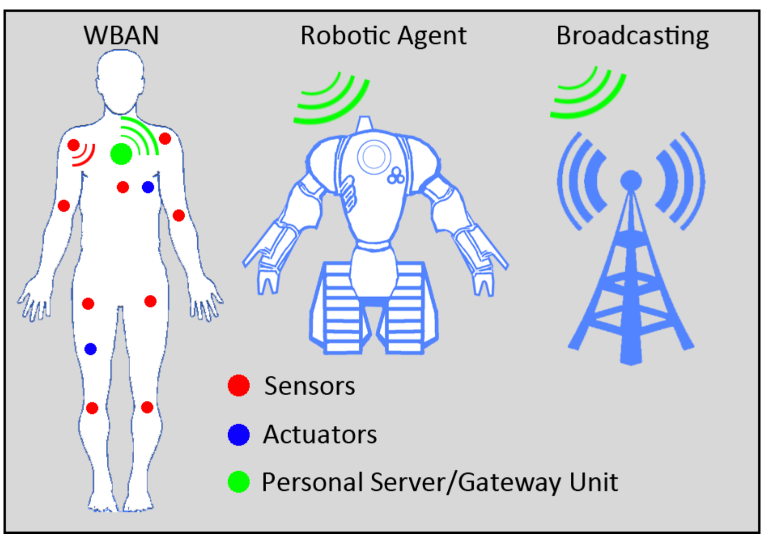

Figure 2: Concept structure of WBAN utilization.

3.1 Capture human activity

The human body is a biological system that is constantly changing. To classify the current state of a human body or determine the state of mind it is essential to gather both physiological and physical data. Section 2.4 presents many of the signals that can be interpreted with a WBAN. Figure 3 illustrates a proposed WBAN with various devices and sensors which can obtain and transmit specific body data. A WBAN can also contain devices for interaction with the human user such as head-mounted displays and headsets.

#	Device	Functionality
1	Personal server	Collect and broadcast acquired data
1	GPS	State position
1	Magnetometer	State orientation
1	Gas sensor	Warn for toxic gases
2	ECG	Monitor heart activity
3	GSR sensor	Read skin conductance
4	Temp. sensor	Monitor finger temperature
5	Motion sensors	Capture body motion
6	Eye Cameras	Observe pupils and eye gaze
6	Head-mounted display	Display information
7	Headset	Provide audio communication

Figure 3: Conceptual WBAN with various devices and sensors.

4 Data acquisition and feature processing

This section describes the green and purple blocks shown in Figure 1 of the system overview.

4.1 The creation of a scenario dataset

This section present the creation of a dataset that was used to train HMMs and they in turn used to classify the corresponding scenario.

When developing a scenario it is important to keep in mind that it should reassemble the real world as much as possible. It can be of interest to consult with professionals in the specific domain that the scenario relates to. For example, if the scenario relates to the domain of emergency rescue operations, experienced people in the domain can be of great assistance to assure an accurate scenario. The same applies to any other scenario whether it is fire or police operations. The creation of a scenario dataset in Scenario Builder involves seven steps. Figure 4 illustrates the approach.

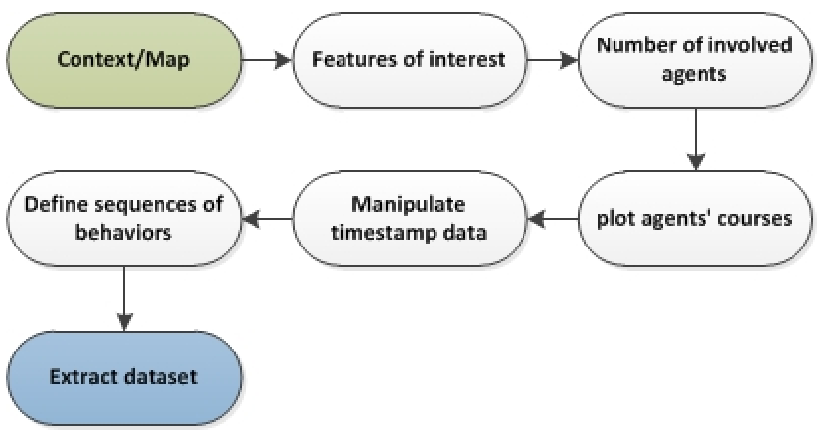

Figure 4: Approach to create a scenario dataset

4.1.1 Scenario context

The scenario context is the environment with its contents where the scenario takes place. In Scenario Builder the world is represented by a map. This map can be artificial or represent a real environment. For this thesis work a GIS map (Geographic information system) over the Swedish city Norrköping was used as context base. When the scenario area has been chosen only a reference to the file location has to be added in Scenario Builder. The map will be displayed in an own view in the program as shown in Figure 5. The scenario context will also contain agents which will move across the map throughout the scenario. The modeling of these agents are explained in Section 4.1.3

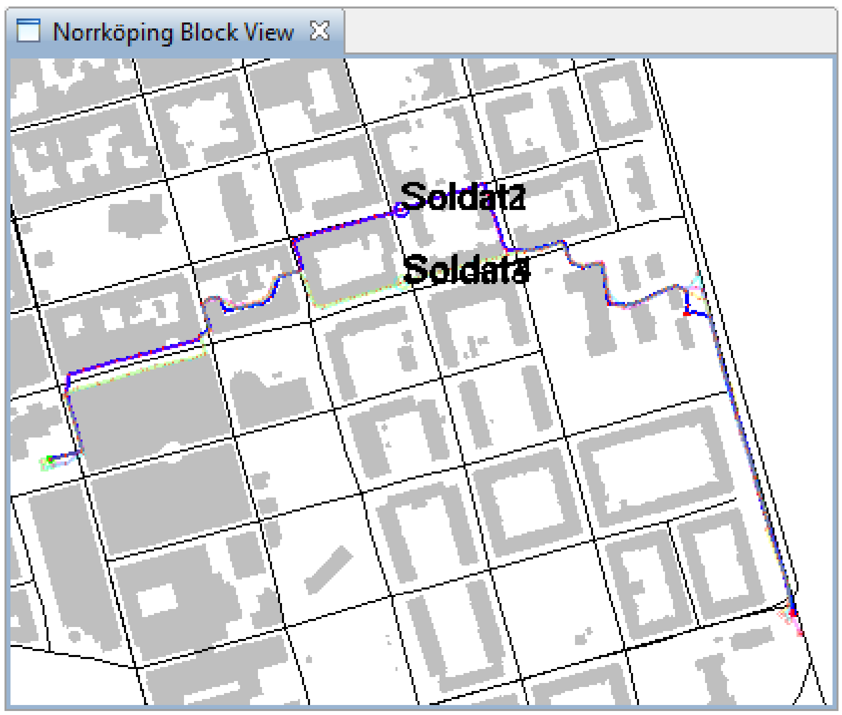

Figure 5: Map View

4.1.2 Features of interest

The features of interest are the features that all agents have. The objective of a scenario creation can differ which leads to different features of interest. The features can be of any kind such as position, skin temperature and orientation. If a needed features is absent it has to be implemented in Scenario Builder in a programmatic manner. The feature processor will later create a dataset in terms of sequences of a scenario.

The values of the features, i.e. the raw data, is shown in a time stamp for each time step of the scenario. Figure 6 displays the so called Scenario Builder View consisting of every agent and their time stamps. The frequency of the time step can be changed to the users preference. Figure 6 also shows that one spatial and one physiological feature is implemented; position and heart rate. The time step is one second.

Some features does not have to be added as features in the Scenario Builder View. These features are features that will be calculated through other features that are added in the Scenario Builder View. One example of such feature is velocity. The velocity of the agent's movement is determined by the length it travels each time step. This means that the velocity can be calculated from position data when the scenario is being exported to a dataset. Other features that are important and calculated during the exportation are relative features. A relative feature is a feature that represents the difference between two agent's feature values. Such as the distance from one agent to another.

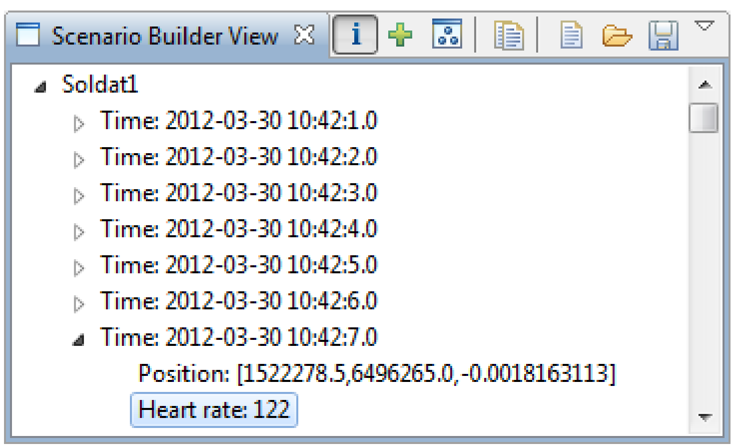

Figure 6: Scenario Builder View

4.1.3 Modeling of agents

The modeling of agents covers three of the seven steps of a scenario creation. It begins by adding the number of involved agents. It is simply done through an "add agent" option. When all agents have been added the courses of the agents can be plotted. This is done be clicking and drawing courses in the map view shown in Figure 5.

After the courses have been plotted, agent features have to be added. A feature is simply added with an "add feature" option. It is not necessary to add a feature for each time stamp because Scenario Builder interpolates between each time step. This simplifies the modeling since a big scenario is likely to have many time stamps. Features that can be added are the features of interest described in the previous section. To manipulate a feature value the user marks the specific feature and edit the value in the Properties View as shown in Figure 7.

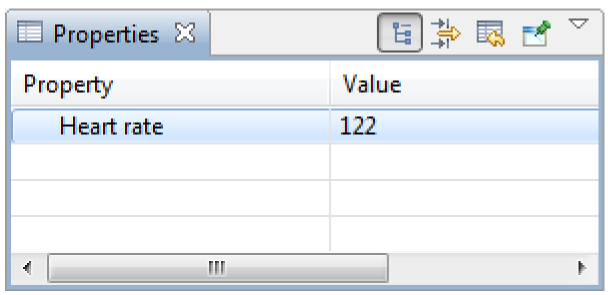

Figure 7: Properties View

4.1.4 Behavior of a sequence

The second last step of the scenario creation is the defining of sequences of behaviors. This is done in the Sequence View shown in Figure 8. The behaviors are defined by the user and can be of any kind such as patrol, rest and group movement to mention a few. In Scenario Builder each behavior is represented by a sequence class. The sequence class in turn contains multiple instances of the same behavior. The specific behaviors which are intended to be classified with the help of the dataset should be defined throughout the whole scenario for as many instances as possible to provide the best result.

To define a sequence class the user first have to define the class name of the specific behavior by using the "add sequence class" option. Once a sequence class of a behavior has been defined specific sequences of the behavior can be added with the "add sequence" option. Thereafter the start and end time for the added sequence can be defined by clicking on a time stamp while the corresponding time label is marked. Once the time span have been defined the agents that are involved in the particular sequence can be added through the "add agent" option. It is only the added agents' time stamp data that will be included in the sequence data. This is important since there often are subgroups in a scenario and it is unlikely that all agents have the same behavior at the same time.

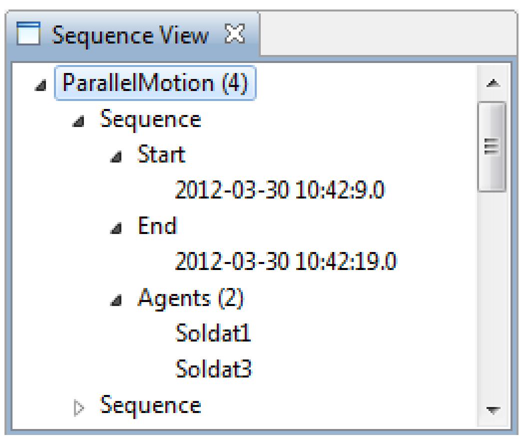

Figure 8: Sequence View

4.1.5 Export feature data

The raw data can be exported to a dataset when the agents are modeled and the sequences of behaviors are defined in the scenario . This is done through the export option. The user can choose which features to include in the dataset and specify the sample rate for the dataset. When the dataset is being created parts of the raw data will be used to generate new features to the dataset using a system dynamics model as illustrated in Figure 9. These are features that are more intangible and difficult to interpret directly. This model is developed outside Scenario Builder and is implemented by referring to the file location of the model. More about the system dynamics model development is described in Chapter 5. The generation of the intangible features is addressed in Section 5.3.

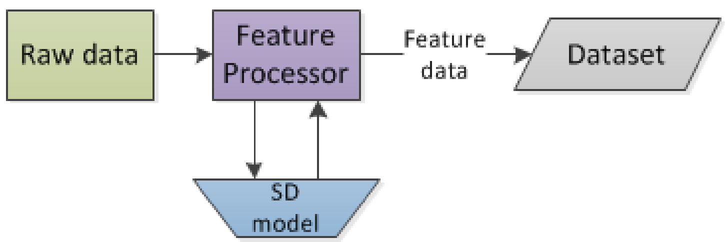

Figure 9: The export process

4.1.6 The extracted dataset

The exported dataset have the file format ARFF (Attribute-Relation File Format) and consists of two separate files. The files are ASCII text files that together describes the instances of the exported behavior sequences. The first file is an information file which holds all the sequence classes and points out where in the second file the corresponding feature data is located. The dataset can be used for any purpose and by any software that can read ARFF files.

5 Extending the feature processor with features of human behavior

5.1 Development of a System Dynamics model

The development of the SD model in this thesis work has been influenced much by two specific previously researched SD models; The MODERE model [25] and the model presented in [52].

The MODERE model captures human motivation and corresponding behavior. Motivation is seen as the process which will lead one to make a certain act. It is difficult to paramatarize a feeling but one could say that a human is more or less prone to act. According to the MODERE model motivation can be parameterized as either 100%, meaning that the human most likely decides to act and 0%, meaning that the chances of acting are very low or the motivation can be somewhere in between.

The research in [52] suggests a model to provide more human-like agents. The model is considered to have the ability to do so by looking at two physiological inputs; heart rate and cortisol level, combined with human perception and mental coping knowledge. A human factor model of stress could provide a prediction of upcoming stress levels unlike the existing stress classifiers that only classifies the current stress level.

However as with many research papers that address human behavior modeling the detailed and mathematical relation of interconnected parameters in the model are not discussed. Only suggestions that possible relations between parameters exist are presented in the research papers. This fact makes it very hard to develop an accurate and adequate model based exclusively on previously published research papers.

Due to the lack of good models with corresponding functions most models, including the one developed in this thesis work, have more or less linear functions. This is however enough to clarify the usefulness of a SD model and the benefits that it can provide.

To develop an adequate and somewhat correct model of human psychophysiologic behavior a real-world sensor data acquisition is necessary. This is discussed further in Chapter 7.

It is important for uniformed personnel to be focused in order to have good performance. Therefore, the SD model developed in this thesis aims at capturing the dynamics between focus, stress and the heart rate. A person is said to be focused if he or she is concentrating on performing one and only one task. However, focus have a broader sense in this thesis. Focus reveals that if an agent is focused the performance level is high and otherwise it is low. The research paper [77] presents a method for affect recognition using physiological signals; heart rate and skin conductance. The research addresses the Yerkes-Dodson law which is of most importance. It explains the relation between arousal, a physiological and psychological state of being awake, and task performance. Figure 10 shows the related function of arousal and task performance, also called Yerkes-Dodson Curve.

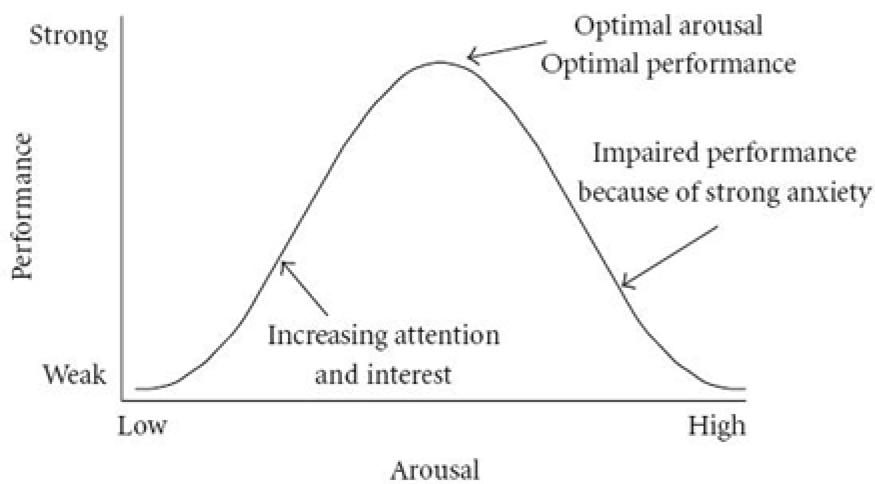

Figure 10: Hebbian version of the Yerkes Dodson Law

Many researchers have suggested that a similar correlation exist between stress and focus which in turn affects task performance. A persons performance can be strong or weak depending on the level of stress and focus. A certain amount of stress have positive effect on a persons level of focus while too much have inhibitory effect.

With the above mentioned taken into account, a SD model has been constructed which is described in the following section.

5.2 A model of stress and focus

It takes a lot of time and elaboration before the resulting SD model is accurate and satisfying. For this thesis work an iterative approach was used which means that the model was enhanced with time until it was finished. The guidelines in Section B.2 was followed in order to get an effective work flow.

The finished model is shown in Figure 11 and the containing parameters is explained in table 3

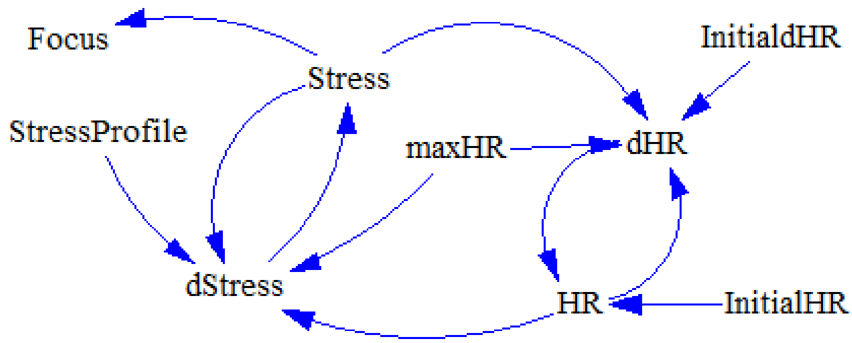

Figure 11: A System Dynamics model of Stress and Focus produced in Vensim

Parameter	Description
HR	Heart rate
Initial HR	The initial heart rate at simulation start.
dHR	derivative of heart rate, ie. at which rate the heart rate increases or decreases.
Initial dHR	The initial rate at which the heart rate increases or decreases at simulation start.
Max HR	States maximum heart rate.
dStress	The rate at which the parameter Stress increases or decreases.
Stress Profile	Calibrates the model according to the characteristics of a persons stress.
Stress	Parameterized value of Stress
Focus	Parameterized value of Focus

Table 3: Components of SD model with corresponding description

It is difficult to parameterize intangible features such as stress and focus. One must estimate how the feature can be represented by a number and how it is influenced by other parameters. It must all together work hand in hand with the whole model. In this model, stress is influenced by heart rate such that if heart rate increases stress increases. The relation between stress and focus have a more complex nature as explained earlier.

Initial heart rate and heart rate derivative are individual parameters in the model because they are determined by a dataset and can therefore not be predetermined.

In order to test the developed SD model one can use the simulation option provided in Vensim. The simulation runs over a certain time period which is set by the user and the result is shown as graphs of each parameters over time. Figure 12 displays a simulation of 20 seconds of the developed SD model. The simulation tool allows you to adjust various parameters in the model in order to understand the behavior of the model.

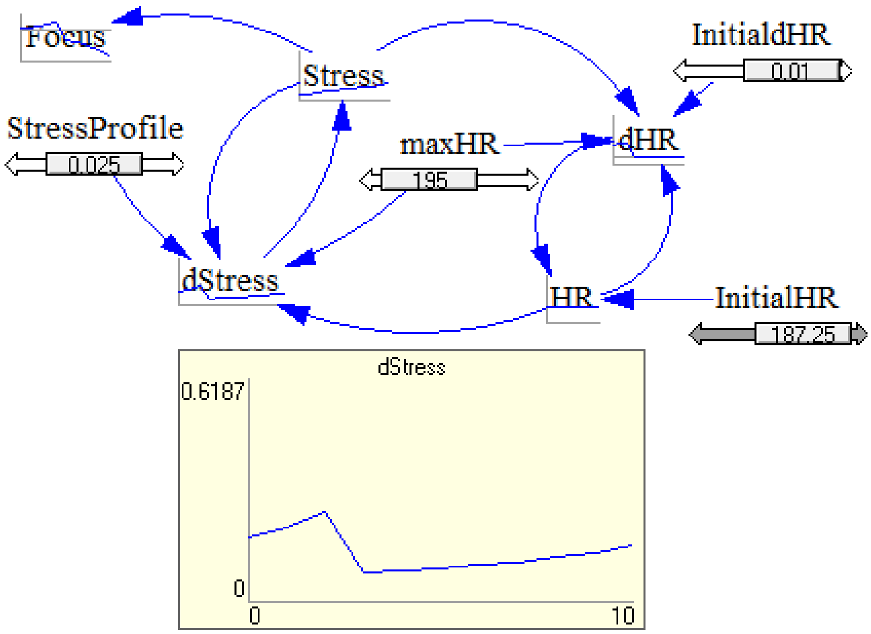

Figure 12: Functions for stress and focus presented in Vensim

Stress if affected by heart rate and corresponding function may look like Figure 13.

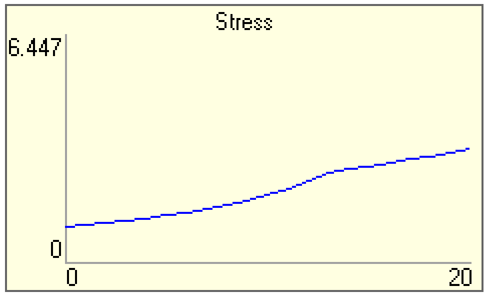

Figure 13: A function over stress (Simulation length: 20 sec.)

As mentioned earlier a certain amount of stress will enhance a persons level of focus while to much stress will do the opposite. The function of focus may look like Figure 14.

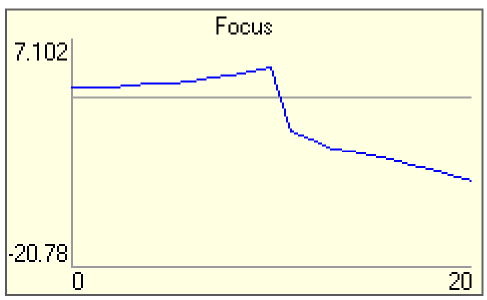

Figure 14: A function over focus (Simulation length: 20 sec.)

Bear in mind that the model described in this section is very simplified compared to the complexity of the real-world system it aims to represent.

5.3 Generation of intangible features

This section explains how the SD model is utilized in order to generate intangible features. As mentioned earlier the process involves a simulation of the model which runs over a predetermined time period.The time period in this particular case is set to 20 steps where each step is 1 second. These are all settings which can be defined in Vensim.

Before the simulation starts the initial values of the model is set according to data from the scenario as shown in Figure 15. After the initial state of the model has been configured the simulation begins.

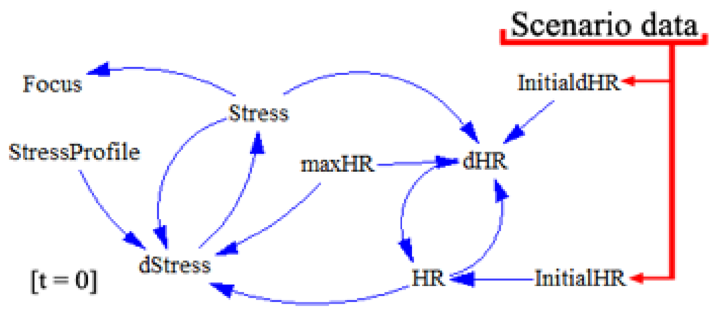

Figure 15: The process of generating new data with a SD model.

The internal parameters are updated dynamically while the simulation is running as the name suggests. When the simulation is finished the values of the parameters that represents the intangible features are extracted and inserted into the dataset as shown in Figure 16.

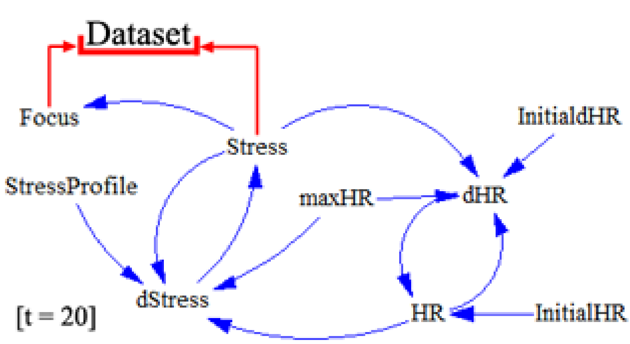

Figure 16: The process of generating new data with a SD model.

Which values from the simulation that is going to be stored in the dataset is configurable .

6 System test and experimental results

6.1 Test Scenario

MOUT (Military Operations in Urban Terrain) scenarios have been of most interest for this thesis due to related research which formed the basis of this work. Military personnel are often exposed at greater risks in an urban terrain due to the lack of sight, mobility constraints and unpredictability of enemy whereabouts. It would therefore be convenient to get support and assistance from a team orientated robotic agent.

6.1.1 The scenario in short

The creation of this scenario is described in Section 4.1

Context base: Norrköping Block

Number of Agents: 4

Time step: 1 Second

Features in Scenario Builder:

- Position
- Heart rate

Behaviors:

- Parallel motion
- Split motion
- Focused line motion
- Unfocused line Motion

The choice of which behaviors to add was made with two purposes in mind. Parallel motion and split motion were mainly added in order to demonstrate the spatial-temporal classification ability of HMMs. Focused and unfocused line motion were added with the purpose of highlighting the impact of the utilized physiological signal and the developed SD model.

The dataset for this scenario has 6 sequences of different instances for each behavior. The time length of a sequence varies from 5 to 25 seconds. The data frequency, which is the time step between data in the sequence is 1 second. Each sequence contains the time stamp data for all involved agents. A time stamp in the dataset consists of 21 features. The number of involved agents in a sequence varies from 2 to 4.

6.2 Experimental setup

The purpose of the experimental setup was to validate the developed recognizer and compare its performance with a standard recognizer. The setup was constructed in RapidMiner and involved; feature selection, HMM learning and a validation process as shown in Figure 17.

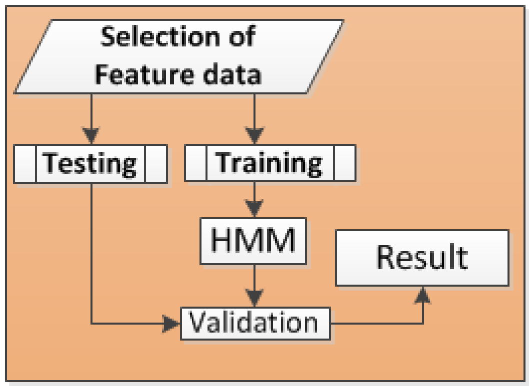

Figure 17: An overview of the experimental setup.

The experiment was conducted several times with different settings and datasets to assure a reliable validation. For each test the parameters inside the operators, such as selected features, were configured to test the consistency of the recognizer. The selectable features are described in Table 4.

The results from a validation in RapidMiner is displayed in confusion matrices which makes it easy to see the characteristics of the recognizer. When both types of recognizers had been tested their average accuracy and specific class precision was compared.

Feature	description
A_Time numeric	The specific time of a time stamp.
A_X/Y/Z numeric	The position in a single coordinate.
A_ANGL_A/B/C/D numeric	A numeric value of the relative angle. between agent A and agent A/B/C/D.
A_ANGL_DISCR_SoldatA/B/C/D	A discrete value of the relative angle. between agent A and agent A/B/C/D.
A_DIST_A/B/C/D numeric	The distance between. agent A and agent A/B/C/D.
A_Velocity numeric	The velocity.
A_HR numeric	The heart rate.
A_dHR numeric	The heart rate derivative.
A_Stress numeric	The stress level.
A_Focus numeric	The focus level.

Table 4: Selection of features for agents A, B, C and D.

6.2.1 Reading the dataset

The first step of the process is to import the dataset and it is done with an import operator block that is set to read ARFF files. Both the information and data file produced by Scenario Builder must be imported in order to interpret the whole dataset. The first two blocks shown in Figure 18 import the dataset information file. The last block in Figure 18 is a cross-validation operator block in which the process continues.

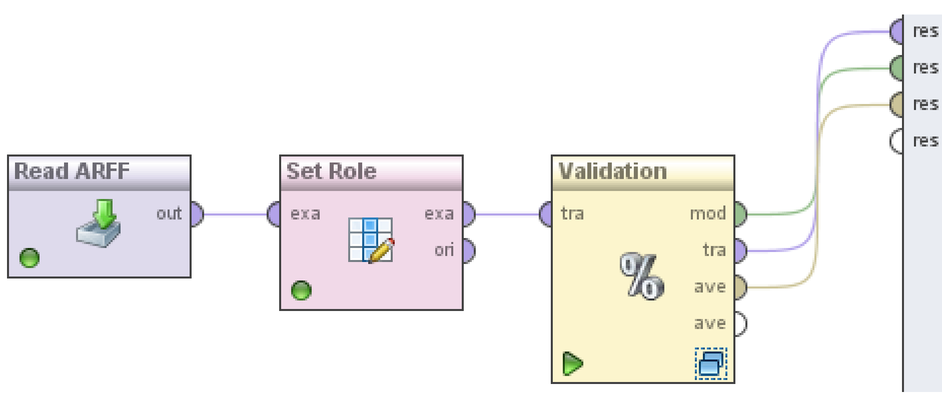

Figure 18: The three outer blocks of the experimental setup

6.2.2 Cross Validation

The cross-validation is divided in to two parts; training and testing. It is a model evaluation method for determining the performance and accuracy of predictive or classification models; HMMs in this thesis. The cross validation type used in this thesis is k-fold cross-validation (10-fold cross-validation specifically). The process of 10-fold cross-validation which is iterative goes as follows. The dataset is randomly divided into 10 subsamples of data, a training set of k-1 samples and a testing sample. The entire dataset is not used for training the HMM in order to avoid classification of data which the HMM already has encountered. Thus, the training set is used for training the HMM as described in Section A.1.3 and the remaining sample is used for testing the trained HMM as described in Section A.1.1.

The process is repeated k number of times and with each of the k subsamples as testing sample exactly once. After the process have been repeated an average result is calculated to produce a single estimation. This reduces the variability of the result.

The first three blocks in the validation block import the data file of the dataset as shown in Figure 19. When the whole dataset has been imported it is time to define which features to train the HMMs with. The user do so by defining a subset of features with a "Select Attribute"-operator block as shown in Figure 20 and described in Section 6.2.3. The last block in the training part of the cross-validation is the actual HMM learning and is described in Section 6.2.4.

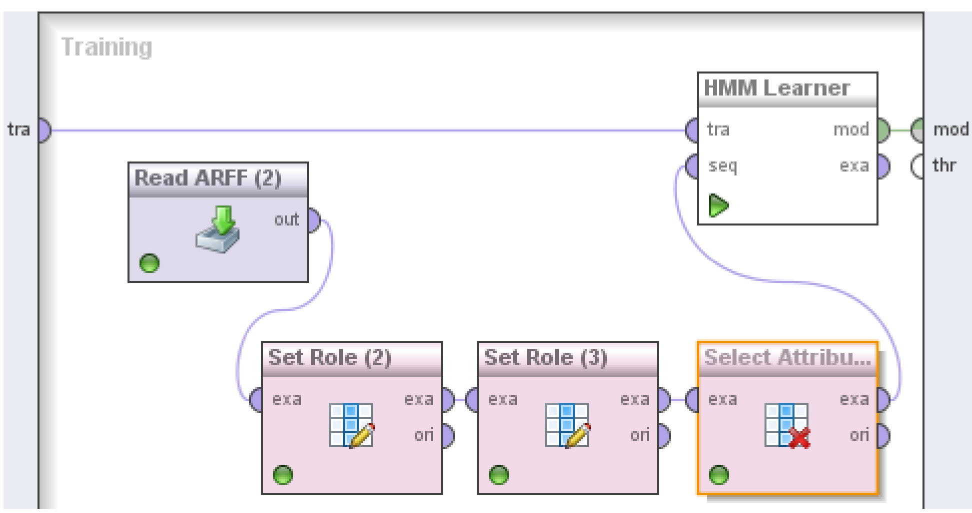

Figure 19: The first part of the cross-validation block

6.2.3 Feature Extraction

The feature processor produce numerous features and not all of them are needed or suitable for training the HMMs with. To determine which features that are of significance one must understand each features influence on the HMMs. Several features may provide exactly the same property and only one of them will be needed in the dataset for training. The best way to figure out which features that are of importance is by testing different sets of features and compare the effects it has on the HMMs classification performance.

The dataset produced in Section 4.1 holds as many as 21 features per agent as mentioned before. Fortunately, RapidMiner provides an easy way to define features of interest as shown in Figure 20.

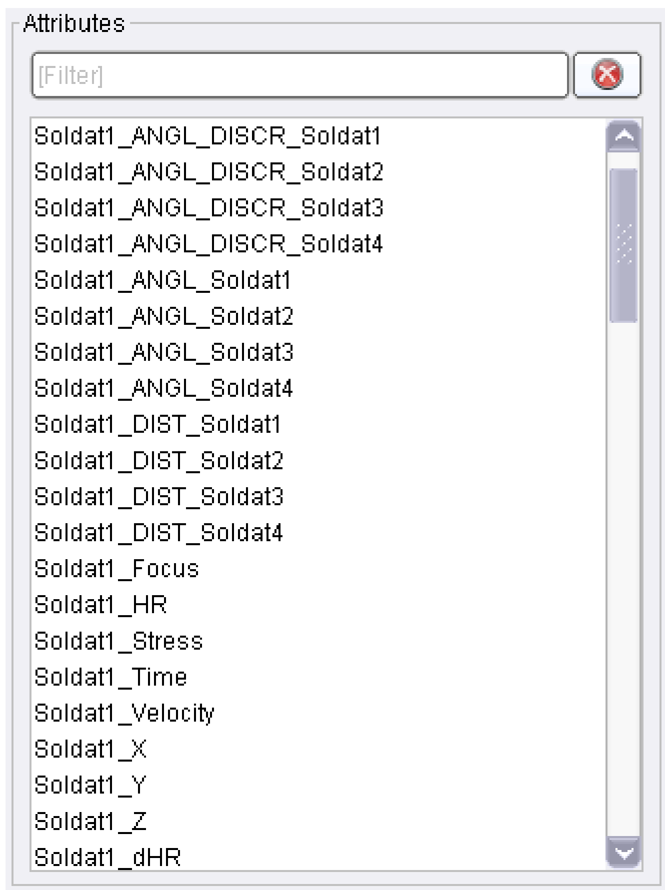

Figure 20: Feature selection.

6.2.4 Machine Learning with Hidden Markov Models

The parameters that can be set in the HMM learner operator block is the number of states, train iterations and gaussian components. All the parameters have major impact on the classification result. A testing approach with different settings for each test is required to achieve a suitable setting with satisfying result. The number of train iterations were most often set to 10 while the other two parameters were manipulated more frequently.

6.2.5 Testing the models

Figure 21 shows the second and last part of the cross-validation block which is the testing. The first operator block applies the trained model on the testing dataset as explained earlier in Section 6.2.2. This means that the model classifies the sequences of behaviors in the dataset originating from Scenario Builder.

The second block in the testing part of the cross-validation is an evaluator operator and is used for classification tasks. It compares the classified and labeled dataset with the actual dataset.

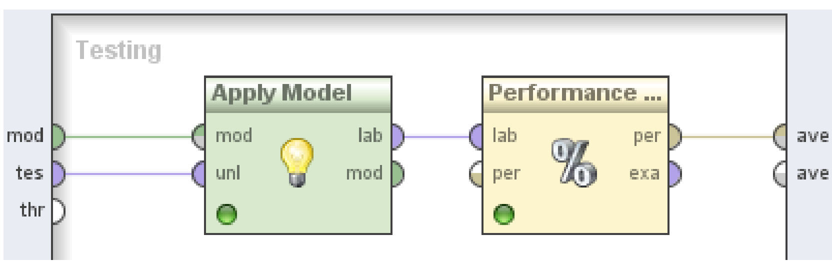

Figure 21: The second part of the cross-validation block

6.2.6 Result

This section presents a brief selection of obtained results generated from tests with the experimental setup. Table 5 presents the average accuracy of classifications based on included features that the HMMs were trained with.

Agents: A, B, C, D

Table 5: Matrix depicting the average accuracy of a model depending on included features.

		Selected							
		1	2	3	4	5	6	7	8
Features	A_X numeric	√				√			
	A_Y numeric	√				√			
	A_Z numeric	√				√			
	A_Time numeric	√				√			
	A_ANGL_A numeric	√				√			
	A_ANGL_B numeric	√				√			
	A_ANGL_C numeric	√				√			
	A_ANGL_D numeric	√				√			
	A_ANGL_DISCR_SoldatA	√				√			
	A_ANGL_DISCR_SoldatB	√				√			
	A_ANGL_DISCR_SoldatC	√				√			
	A_ANGL_DISCR_SoldatD	√				√			
	A_DIST_A numeric	√				√			
	A_DIST_B numeric	√	√	√	√	√	√	√	√
	A_DIST_C numeric	√	√	√	√	√	√	√	√
	A_DIST_D numeric	√	√	√	√	√	√	√	√
	A_Velocity	√	√	√	√	√	√	√	√
	A_HR numeric	√				√			
	A_dHR numeric	√				√			
	A_Stress numeric	√			√	√			√
	A_Focus numeric	√		√	√	√		√	√
	# of States in HMM	5	5	5	5	6	6	6	6
	Gaussian components	4	4	4	4	5	5	5	5
	Time in SD model (sec)	10	10	10	10	20	20	20	20
	Average accuracy (%)	26.4	86.8	90.8	85.9	29.5	77.7	89.5	88.6

Table 6 presents the result from test 1 in Table 5 where all features in the dataset were selected.

Table 6: Confusion matrix depicting agent activity recognition performance.

			True				Precision
			a	b	c	d	(%)
Predicted	Parallel motion	a	3	3	5	7	16.67
	Split motion	b	6	6	7	3	27.27
	Focused line motion	c	5	2	10	6	43.48
	Unfocused line motion	d	6	8	5	2	9.52
	Recall (%)		15.0	31.58	37.04	11.11	

Table 7 presents the result from test 2 in Table 5 where only spatial features were selected.

Table 7: Confusion matrix depicting team activity recognition performance.

			True				Precision
			a	b	c	d	(%)
Predicted	Parallel motion	a	19	0	0	0	100.0
	Split motion	b	1	19	0	11	61.29
	Focused line motion	c	0	0	27	0	100.0
	Unfocused line motion	d	0	0	0	7	100.0
	Recall (%)		95.0	100.0	100.0	38.89	

Table 8 presents the result from test 3 in Table 5 where both spatial features and focus were selected.

Table 8: Confusion matrix depicting agent activity recognition performance.

			True				Precision
			a	b	c	d	(%)
Predicted	Parallel motion	a	20	6	0	0	76.92
	Split motion	b	0	13	0	1	92.86
	Focused line motion	c	0	0	27	0	100.0
	Unfocused line motion	d	0	0	0	17	100.0
	Recall (%)		100.0	68.42	100.0	94.44	

Table 9 presents the result from test 6 in Table 5 where only spatial features were selected.

Table 9: Confusion matrix depicting agent activity recognition performance.

			True				Precision
			a	b	c	d	(%)
Predicted	Parallel motion	a	18	0	0	0	100.0
	Split motion	b	2	19	0	13	55.89
	Focused line motion	c	0	0	27	0	100.0
	Unfocused line motion	d	0	0	0	5	100.0
	Recall (%)		90.0	100.0	100.0	27.78	

Table 10 presents the result from test 7 in Table 5 where both spatial features and focus were selected.

Table 10: Confusion matrix depicting agent activity recognition performance.

			True				Precision
			a	b	c	d	(%)
Predicted	Parallel motion	a	19	2	0	0	90.48
	Split motion	b	1	12	0	0	92.31
	Focused line motion	c	0	0	27	0	100.0
	Unfocused line motion	d	0	5	0	18	78.26
	Recall (%)		90.0	63.16	100.0	100.0	

6.3 Discussion

The result in Table 5 shows clearly that the intangible features enhance the average classification accuracy of behaviors. The table also clarifies that the usage of all features will decrease the performance of the classification dramatically. This suggests that when more features are used the feature space is increased and this affect the classification negatively. Thus, the predictive power reduces as the dimensionality increases. This phenomena is called the curse of dimensionality and in the machine learning domain specifically it is known as the Hughes effect or Hughes phenomenon [32] . The size of the dataset i.e. the amount of data that is needed to provide a good result often grows exponentially with the dimensionality. A larger dataset would most likely provide a better result when all features are selected.

However, this thesis does not suggests the usage of a large number of features even if a very large dataset is provided since the classification would be more time consuming. The real-time classification in a robotic agent most be rapid and still have high accuracy. Therefore it is preferable to use a lower number of features which have high importance and still provides an accurate classification.

Table 5 also shows that a combination of the stress and focus feature lower the average accuracy slightly. One reason for this can be the structure of the SD model. Tests in the particular case have shown that a combination of the features enhance the classification of behaviors that are more intangible and impairs the classification of behaviors that can be classified only through spatial data. A model with more accurate relationships would likely erase this flaw.

The results also show that recognizers with different HMM settings are consistent, i.e. the precision and recall percentage of the classes are kept at a similar level. See Tables 7, 8, 9 and 10.

6.3.1 Stand alone HMM compared with SD model extension

This section discuss the comparison of the already existing method of using HMMs exclusively for classification and the suggested approach with a SD model extension. In the overview of the system illustrated in Figure 1 this means without and with the blue block respectively.

Table 7 shows that a recognizer with a HMM stand alone approach have difficulties to classify unfocused line motion. Table 8 on the other hand highlights that the recognizer extended with the SD model enhance the intangible behavioral classification. The two tables also show that the extended system do so at the cost of the spatial behavioral classification accuracy. Further tests with more instances of the same behaviors in the dataset indicated that this most likely was a result of an insufficient amount of training data. Thus, it is very important that the recognizer is trained with a sufficient amount of data. To determine if the dataset is big enough one can estimate the needed data amount based on the number of selected features. It is however easier to avoid this by decreasing the amount of selected features if possible. For each selected feature the amount of needed of training data is increased dramatically.

In order to assess more complex and intangible behaviors a more sophisticated SD model must be applied to the recognizer. It would for instance be convenient to have features for motivation and anxiety. With such and similar features it would be possible for a recognizer to classify a wider variety of intangible human behaviors. A robot equipped with such recognizer could in turn achieve a much better human understanding and provide reliable decision support. For example, if a team member is facing a demanding task the robot could determine if the member is the most suitable of the members to perform the specific task.

6.3.2 Datasets

The datasets that was utilized fulfilled its purpose and was sufficient enough to prove the advantage of the extended recognizer. However, a real-world dataset would have reflected the true performance of the recognizer. That however would be much more time consuming to implement and would not provide the same flexibility. At an early state of the development of this type of recognizer it is good to have the ability to customize the datasets.

6.3.3 Stress profile

Another essential issue to discuss is the fact that all intangible features of the agents are generated with the same model. In real life this is not the case since all people react differently in situations. An individual stress profile for each agent, i.e. team member, would be necessary to improve the classification process and get a more real life depiction. It seems more or less impossible to find a stress model that is general for all team members. The model developed in this thesis is as mentioned before merely an estimation of the bodily behaviors. It is only good enough to prove the usefulness of an SD model in team behavior classification.

7 Conclusions

In this thesis we improved existing teamwork activity recognizers by utilizing a physiological signal and a SD model which allowed the recognizer to better classify intangible activities. The proposed method has been proven useful and is believed to have significance for future teamwork activity recognizers and team orientated robots. Specifically, the proposed SD model utilizes the physiological signal heart rate to interpret intangible features such as agents' level of stress and focus. These features in turn are used to distinguish more intangible behaviors from spatial behaviors. a SD model does not only enables interpretation of intangible features but also provides the ability to predict how a scenario may evolve based on initial circumstances and simulation time. As part of this, a data acquisition tool has been developed in order to produce artificial datasets for testing purposes. The results from the system tests have been analyzed and compared with former methods. The outcome is that an accurate SD model is able to classify a wider amount of human behaviors.

The thesis has also proposed a conceptual approach of how robots can interpret human behaviors by the utilization of WBAN. The concept is believed to be of importance in order to establish a real time classification of human behaviors and in turn achieve robots with sufficient human awareness.

Robotics with more human awareness would lead to a whole new era of human robot interaction and robotics applications. Most robots today have a lack of perception and cannot provide the needed feedback that a human team demands.

The literary study in this thesis indicates that comprehensive knowledge from several research domains must be applied in order to enhance the human awareness of a team oriented robot. Some of the subjects that have been visited during the thesis work are: Machine Learning (activity recognition), System Dynamics, Robotics, Artificial Intelligence, Human-Robot-Interaction, Psychology, Physiology and Sensor Systems (WBAN).

7.0.4 Future Work

As far as the author knows, no one has never developed a concrete SD model of human psychophysiologic behavior based on real-world sensor data. Such a model would provide a much more accurate and true model of human psychophysiologic behavior. The model would in turn have better qualifications of enhancing the human awareness of a robot. The development of an accurate and adequate model would start by collecting real-world sensor data with a WBAN as suggested in Section 2.5. With the collected data it would be possible to develop an extensive SD model with adequate relationships between interconnected parameters.

It is also essential to expand the usage of physiological signals in the system. A first step would be to integrate a GSR feature since it has high co-occurrence with stress and reveals a lot about the state of mind. It would be desirable to utilize all the signals provided by the WBAN presented in Section 1.6.3. Therefore, it would optimal to realize a functional WBAN with all its sensors which would provide body data to a robot. Once the suggested WBAN has been constructed it can be used to collect real-world data which would be assembled into datasets. The datasets would in turn be used in the already implemented validation process to validate the developed recognizer with real-world data.

To further improve the classification of human team behaviors and individual behaviors the stress profile mentioned in Section 6.3.3 must be addressed and developed. This has to be done by observing individual stress impact and management and the development of a customized and unique SD model for the specific individual. This applies to all features that can be of interest, stress is just one out of many.

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A Hidden Markov Models

In a Markov Model we have a set of states in which one of these states the Markov process starts. It then moves successively from one state to another but it can also go to itself again. These moves are called transitions or steps and have a probability associated to it. This transition probability states how likely it is that a transition from one state to another is made. A graphical model of this is shown in Figure 22.

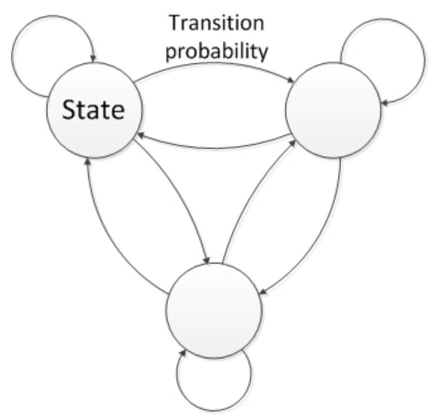

Figure 22: An example of a three-state markov model.

A state is denoted $\omega(t)$.

A sequence of states with length T is denoted $\omega^T = \{\omega(1), \omega(2), ..., \omega(T)\}$

The transition probability between states are denoted with a_{ij} where the transition occurs between state i and j.

$$a_{ij} = P\left(\omega_j\left(t+1\right) \mid \omega_i\left(t\right)\right) \tag{1}$$

The sum of the transition probabilities from a state must be 1.

$$\sum_j a_{ij} = 1$$

The simplest Markov Model is the **First-Order Markov chain**. In this model the future only depends on the present state and is independent of the past. You could say that the First-Order Markov chain is memoryless. This property of the Markov Model is called the **Markov property**. The fact that first order Markov models only depends on the current state makes it a bad choice for classifying sequential data that represent a behavior. Therefore a more suitable model must be used, namely HMMs.

HMMs also consists of states that have possible transitions to other states but there is also emission probabilities in each state which are the probabilities that in a particular state, these particular outputs are emitted. The emission probability is sometimes called observation probability pointing to that the emitted output is observable. Each state have the same set of possible outputs. In a HMM the internal states are hidden from the observer and only the output that is emitted from the state is observable. The emission probability can be denoted with b_{jk}.

$$b_{jk} = P\left(\upsilon_k\left(t\right) \mid \omega_j\left(t\right)\right) \tag{2}$$

Figure 23 illustrates the observable part of a HMM.

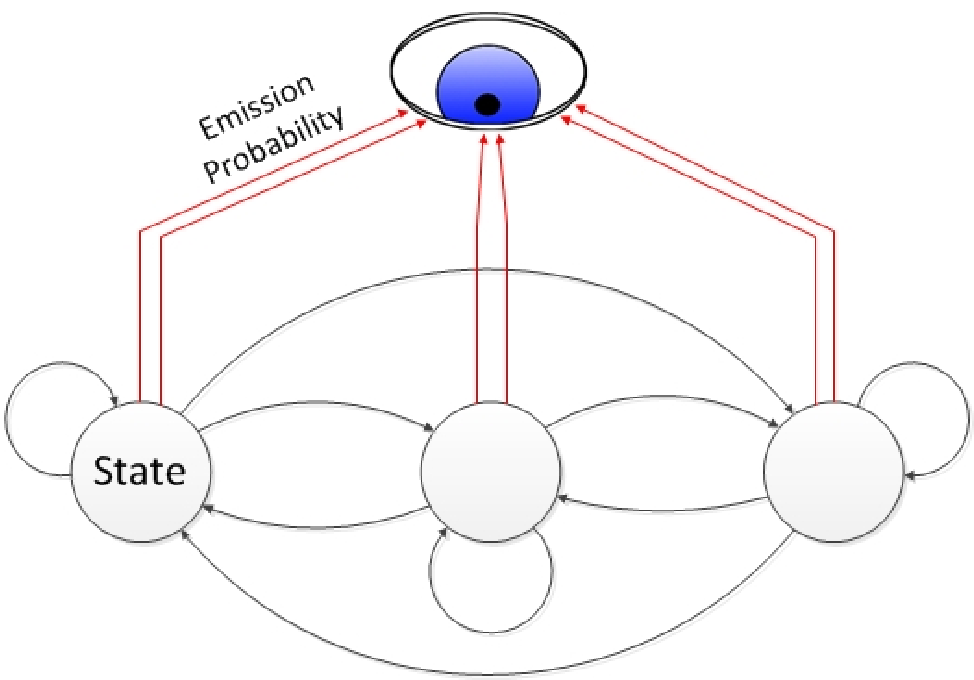

Figure 23: Only the emitted output is observable.

Each state has a probability distribution over possible outputs. A sequence of these outputs shows us the state sequence of the process which otherwise is hidden. Thus, a sequence of observations gives us the state sequence through which a process passes. These observations can be placed into a feature vector. From this vector we can try to determine the state sequence of the process. A sequence of visible states can be denoted V^T where T is the length of the sequence.

$$V^T = \{v(1), v(2), ..., v(T)\}$$

Just like the transition probability the emission probability of a state must sum up to 1.

$$\sum_k b_{jk} = 1$$

A HMM is easier explained with an example. In this example the HMM has two internal states with possible transitions between them and the the possibility of emitting one of three outputs at a given time. The two internal states are Sunny and Rainy and the three possible and visible outputs are Walk, Shop and Clean. Imagine you live far away from your friend and you speak over the phone everyday about what she has done during the day. You are then going to determine whether it is sunny or rainy at your friends place depending on what activity your friend has been doing. The activities represents the visible outputs. Figure 24 describes the HMM of the scenario. The numbers are randomly assigned for this example.

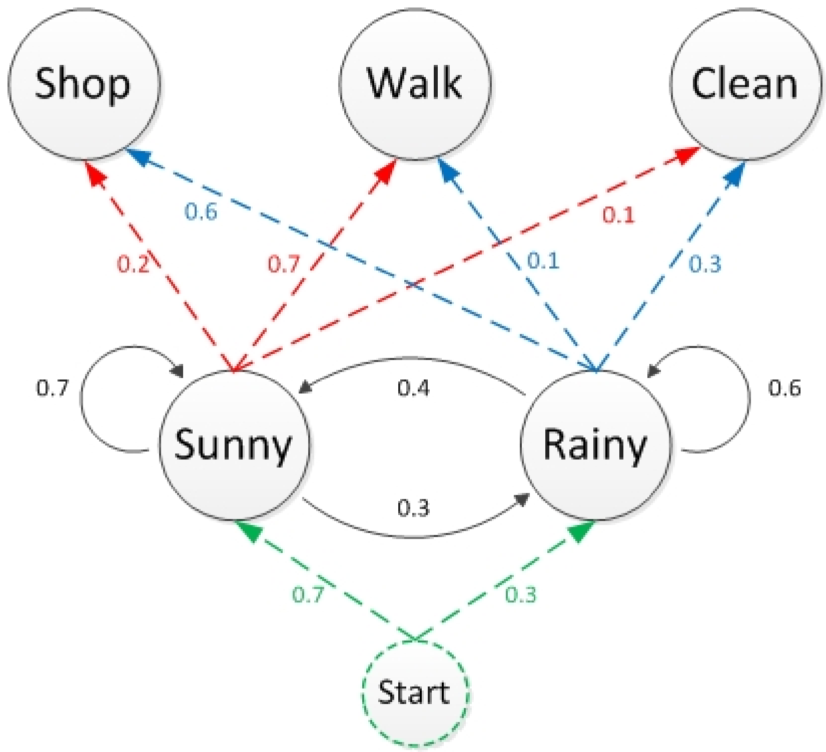

Figure 24: Example of a HMM with numbers.

Start is not a state, it only shows the probability of where the process will start. Thus, it is the current weather when you receive the first call from your friend. In the example in Figure 24 the HMM tells us for example that if it is sunny it is a 70% chance that your friend is out walking.

To get an overview of the HMM transition probabilities the transition probabilities can be arranged in a matrix.

$$a_{ij} = \begin{bmatrix} & Sunny & Rainy \\ Sunny & 0.7 & 0.3 \\ Rainy & 0.4 & 0.6 \end{bmatrix}$$

Just like the transition probabilities the emission probabilities can be arranged in a matrix.

$$b_{jk} = \begin{bmatrix} & Shop & Walk & Clean \\ Sunny & 0.2 & 0.7 & 0.1 \\ Rainy & 0.6 & 0.1 & 0.3 \end{bmatrix}$$

A.1 Utilization of Hidden Markov Models

To utilize the functionality of Hidden Markov Models we must understand some processes. These processes are;

- Evaluation
- Decoding
- Learning

A.1.1 Evaluation

In the evaluation we want to determine the probability that a particular sequence V^T of T visible outputs $v(t)$ was generated from a known HMM. With a known HMM we mean a HMM were the transition and emission probabilities are known. Thus, given a HMM Θ and a sequence of visible outputs V^T, we want to find $P\left(V^T \mid \Theta\right)$.

The probability that a particular sequence of visible outputs V^T was produced by a particular HMM is

$$P\left(V^T \mid \Theta\right) = \sum_{r=1}^{r_{max}} P\left(V^T \mid \omega_r^T\right) P\left(\omega_r^t\right) \tag{3}$$

In equation (3) ω_r^T is a sequence of hidden sates where T is its length and r indexes the specific sequence. The summation consider all possible sequences of length T.

The second factor in equation (3) describes the transition probability a_{ij} for the hidden states and can be written as

$$P\left(\omega_r^T\right) = \prod_{t=1}^{T} P\left(\omega\left(t\right) \mid \omega\left(t-1\right)\right) \tag{4}$$

Equation (4) gives us the product of the transition probabilities according to the hidden sequence.

Since the output probabilities only depends on the hidden state the first factor in equation (3) can be written as

$$P\left(V^T \mid \omega_r^T\right) = \prod_{t=1}^{T} P\left(v\left(t\right) \mid \omega\left(t\right)\right) \tag{5}$$

Equation (5) gives us the product of the emission probabilities according to the hidden state and its possible outputs.

Equation (3) can now be written with equations (4) and (5) as

$$P\left(V^T \mid \Theta\right) = \sum_{r=1}^{r_{max}} \left(\prod_{t=1}^{T} P\left(v\left(t\right) \mid \omega\left(t\right)\right) P\left(\omega\left(t\right) \mid \omega\left(t-1\right)\right) \right) \tag{6}$$

Equation (6) says that the probability that a particular sequence V^T of T visible outputs $v(t)$ was generated from a known HMM Θ is equal to the sum over all possible hidden state sequences of the probability that a particular transition was made multiplied by the probability that is then emitted the observed output in the sequence V^T.

We can calculate equation (6) recursively because each term in the summation only depends on the observed output $v(t)$, the state $\omega(t)$ and the previous state $\omega(t-1)$.

To better under stand the recursive algorithm we first denote that $\alpha_j(t)$ is the probability that a HMM is in a hidden state ω_j at time t and have generated the first t elements of the sequence V^T. **The Forward Algorithm** is used to calculate the probability and is shown in algorithm 1.

Algorithm 1 The Forward Algorithm

Initialization $t \leftarrow 0, a_{ij}, b_{jk}, \alpha_j(0)$, observed output sequence V^T

  for $t = 0 \rightarrow t = T$ **do**

    $t \leftarrow t + 1$

    $\alpha_j(t) \leftarrow b_{jk} v(t) \sum_i \alpha_i(t-1) a_{ij}$

  end for

  return $P\left(V^T \mid \Theta\right) \leftarrow \alpha_0(T)$

There is a time-reversed version of the forward algorithm called the Backward Algorithm which begins at the last output in the observed output sequence and iterates backwards to the first output. The Backward Algorithm is shown in algorithm 2.

Algorithm 2 The Backward Algorithm

Initialization $t \leftarrow T, a_{ij}, b_{jk}, \beta_j(T)$, observed output sequence V^T
  for $t = T \rightarrow t = 1$ **do**
    $t \leftarrow t - 1$
    $\beta_j(t) \leftarrow \sum_i \alpha_i(t+1) a_{ij} b_{jk} v(t+1)$
  end for
  return $P\left(V^T \mid \Theta\right) \leftarrow \alpha_0(T)$

A.1.2 Decoding

The main goal with the decoding is to with a known HMM Θ and a sequence V^T of observed outputs determine the most likely sequence ω^T of hidden states that led to the observed output sequence. Thus, we want to find the specific sequence ω^T that maximize $P\left(V^T, \omega^T \mid \Theta\right)$. The decoding algorithm is shown in algorithm 3

$$P\left(V^T, \omega^T \mid \Theta\right)_{max} = \alpha_j(t)_{max} \tag{7}$$

$$\alpha_j(t) = b_{jk} v(t) \sum_i \alpha_i(t-1) a_{ij} \tag{8}$$

$$\alpha_j(t)_{max} = argmax \alpha_j(t) \tag{9}$$

For clarity we take an example. Imagine that you know what your friend from the last example did the past four days. Now you want to figure out what kind of weather it most likely was during those four days. The first day your friend was out walking, the second day shopping, the third day cleaning and the last day your friend was out walking.
For each time step we look for the state $\omega(t)$ with the highest probability $\alpha_j(t)_{max}$ of having originated from the previous state $\omega(t-1)$ in which the observed output $v()$ could have been generated. Thus, the sequence of these hidden states $\{\omega(1), \omega(2), ..., \omega(T)\}$ is the state path of the specific process. In our example shown in Figure 25 the possible path is$\{Sunny, Sunny, Rainy, Sunny\}$

To begin with we assume that the process starts in the state "Sunny" since it has the highest probability of being the state when the your friend is out walking. Equation (10) shows one step in the decoding process. Note that this is the same procedure as in the forward algorithm.

$$\alpha_1(1)) = 1 \times \mathbf{0.7} \times \mathbf{0.2} = 0.14 \tag{10}$$

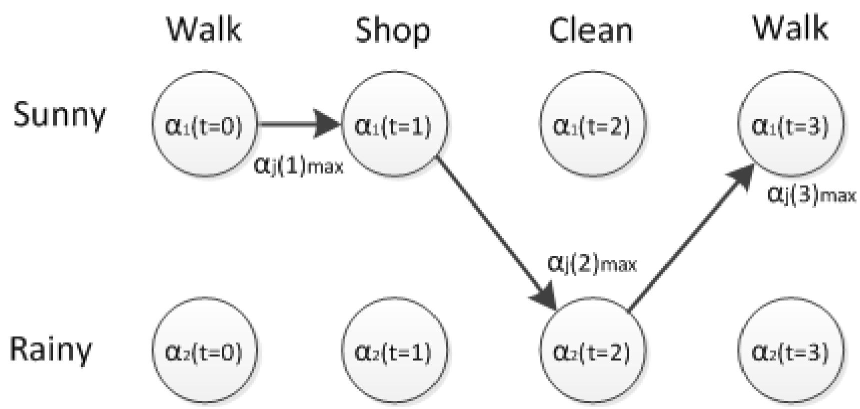

Figure 25: Example of a possible sequence of hidden states that could have generated the output sequence. A graph like this is called a trellis.

$$a_{ij} = \begin{array}{cc} & \begin{array}{cc} Sunny & Rainy \end{array} \\ \begin{array}{c} Sunny \\ Rainy \end{array} & \begin{bmatrix} \mathbf{0.7} & 0.3 \\ 0.4 & 0.6 \end{bmatrix} \end{array}$$

$$b_{jk} = \begin{array}{cc} & \begin{array}{ccc} Shop & Walk & Clean \end{array} \\ \begin{array}{c} Sunny \\ Rainy \end{array} & \begin{bmatrix} \mathbf{0.2} & 0.7 & 0.1 \\ 0.6 & 0.1 & 0.3 \end{bmatrix} \end{array}$$

The next probability is calculated in the same way in equation (11).

$$\alpha_2(1)) = 1 \times \mathbf{0.3} \times \mathbf{0.6} = 0.18 \tag{11}$$

Now we can determine $\alpha_j(1)_{max}$ and continue on the path with the highest probability. The full path is shown in Figure 26.

Figure 26: A trellis with red arrows showing the most likely path of the hidden sequence

Algorithm 3 The Decoding Algorithm

Initialization $\omega^T \leftarrow \{\}, t \leftarrow 0$
  for $(t \leftarrow t+1) \rightarrow t = T$ **do**
    $j \leftarrow j+1$
    for $(j \leftarrow j+1) \rightarrow i = I$ **do**
      $\alpha_j(t) = b_{jk}v(t)\sum_i^I \alpha_i(t-1)a_{ij}$
    end for
  $j' = \arg\max \alpha_j(t)$
  $\omega^T \leftarrow j'$
  end for
  return ω^T

A.1.3 Learning

The learning part is used when the internal and visible states of a HMM are known but not the transition and emission probabilities. By utilizing a sequence of observable training data (observed outputs) we want to determine these probabilities a_{ij} and b_{jk}. One learning algorithm is the Baum-Welch algorithm, also called the Forward-Backward algorithm which will be explained in this section. Baum-Welch algorith is a type of generalized expectation-maximization algorithm. This means that the algorithm iteratively adjusts the internal parameters a_{ij} and b_{jk} of the HMM θ such that it is maximized. The forward and backward algorithm can be utilized to calculate the maximum probability.

A.1.4 Baum-Welch algorithm

In the previous section we defined $\alpha_i(t)$ to be the probability that the model is in a state $\omega_i(t)$ and has generated the observed output sequence up to time step t. In a similar manner we can describe the probability that the model is in a state $\omega_i(t)$ and will generate the remaining outputs of the observed sequence, $v(t+1) \rightarrow v(T)$. We denote this probability as $\beta_i(t)$ and define it as (12).

$$\beta_i(t) = \sum_j \beta_j(t+1) a_{ij} b_{jk} v(t+1) \tag{12}$$

Equation (12) says that the probability $\beta_i(t)$ that the model will generate the remaining output sequence is the sum of the probability of making a transition to the next state $\omega_j(t+1)$ multiplied with the probability that this hidden state emitted the correct observable output. Thus, we are going backwards in our sequence of hidden states.

There are two cases where equation (12) does not apply. The first exception is if we are at the final time step T and want to find out the probability $\beta_t(T)$ and the state $\omega_i(T)$ is not the final state of the sequence.

$$\beta_i(t) = 0 \qquad (if \quad \omega_i(t) \neq \omega_0 \;\; and \;\; t = T) \tag{13}$$

The second exception is if we are at the final time step T and want to find out the probability $\beta_t(T)$ and the state $\omega_i(T)$ is the final state of the sequence.

$$\beta_i(t) = 1 \qquad (if \quad \omega_i(t) = \omega_0 \;\; and \;\; t = T) \tag{14}$$

Imagine that we know $\alpha_i(t)$ up to time step $T-1$ and we want to determine $\beta_t(T)$. Then we would have equation (15)

$$\beta_i(T-1) = \sum_j \beta_j(T) a_{ij} b_{jk} v(T) \tag{15}$$

By repeating this procedure we can determine $\beta_t(T-2)$ and so on backward in the trellis.

But one must remember that $\alpha_i(t)$ and $\beta_t(T)$ are just estimates of the real values since we do not know the real values for a_{ij} and b_{jk}.

We will now look at a way to better estimate these probabilities. We first define a new probability as in (16).

$$\varepsilon_{ij}(t) = \frac{\alpha_i(t-1) a_{ij} b_{jk} \beta_j(t)}{P(V^T \mid \theta)} \tag{16}$$

This is the probability that we are in a state $\omega_i(t-1)$ and make a transition to state $\omega_j(t)$ given that the model has generated the given training sequence. $P(V^T \mid \theta)$ is simply the probability that the model by any path generated the given output sequence. With other words it is the forward algorithm shown in algorithm (1).

Now we can denote the estimated transition probability between state $\omega_i(t-1)$ and $\omega_j(t)$ to be $\hat{a}_{ij}$ and define it as equation (17).

$$\hat{a}_{ij} = \frac{\sum_{t=1}^{T} \varepsilon_{ij}(t)}{\sum_{t=1}^{T} \sum_k \varepsilon_{ik}(t)} \tag{17}$$

Thus, $\hat{a}_{ij}$ is the ratio between the expected number of transitions between state $\omega_i(t-1)$ and $\omega_j(t)$ at any time in the given sequence and the number of total expected transitions from $\omega_i(t)$ to any other state.

The estimated emission probability that a particular output $v(t)$ is generated is denoted $\hat{b}_{jk}$ and defined in equation (18).

$\hat{b}_{jk}$ is defined as equation (18)

$$\hat{b}_{jk} = \frac{\sum_{t=1}^{T} \sum_l \varepsilon_{jl}(t)}{\sum_{t=1}^{T} \sum_l \varepsilon_{jl}(t)} \qquad where \quad v(t) = v_k \tag{18}$$

$\hat{b}_{jk}$ is the ratio between the expected number of times a particular output v_k is generated from state ω_j and the expected times state ω_j is visited.

By utilizing equation (17) and (18) we can calculate improved transition and emission probabilities based on the given model and the observed sequence V^T. The calculations can be repeated until the probability values is satisfying a criterion. The criterion is a boundary saying that the calculations will repeat until the probability values does not change sufficiently much.

The pseudo-code for the Baum-Welch algorithm is shown in algorithm (4)

Algorithm 4 The Baum-Welch Algorithm

Initialization $V^T, a_ij, b_jk, \lambda \ \ (convergence \ \ criterion), x \leftarrow 0$

  for $(x \leftarrow x+1) \rightarrow max[a_ij(x) - a_{ij}(x-1), b_{jk}(x) - b_{jk}(x-1)] < \lambda$ **do** to

    compute $\hat{a}_{ij}(x)$ with $a(x-1)$ and $b(x-1)$ Eq.(17)

    compute $\hat{b}_{jk}(x)$ with $a(x-1$ and $b(x-1)$ Eq.(18)

    $a_{ij}(x) \leftarrow \hat{a}_{ij}(x-1)$

    $b_{jk}(x) \leftarrow \hat{b}_{jk}(x-1)$

  end for

  return $a_ij \leftarrow a_ij(x)$ and $b_jk \leftarrow b_jk(x)$

B System Dynamics

There are dynamics in every system which has mutual interaction within the system. To predict the behavior of a dynamic system over a period of time it is important to understand the structure of the system. In this chapter we will discuss a method for modeling such a dynamical system. Specifically we are going to investigate how so called System Dynamics models (SD models) can be utilized for this purpose. In a SD model it is easy to understand and follow the system over time. It is a graphical map over constituent components of a system and describes their interactions and behaviors.

When a component in a dynamic system changes it will influence connected components. This means that one change will cause other components to change and those components will in turn affect its connected components and so on. In most systems this chain of reaction will take place in a loop, meaning that one component that changes will influence itself over time.

In System Dynamics loops are called feedback loops due to the fact that components have feedback to its point of origin. Feedback loops are an important part of System Dynamics.

Another part that have a major impact on the behavior of a dynamic system is the internal time delays between components. That is the time it takes for one component to affect a connected neighbor component. By capturing the relationships between system components, i.e. time delays and interdependencies, we can analyze and design systems more accurately.

An important aspect when analyzing or designing dynamic systems is that minor parts of a system may behave in a totally different manner when it is connected to the entire system. One must keep in mind that in some cases the whole system cannot be explained in terms of the behavior of its minor parts. Therefore, it is crucial in System Dynamics to establish convenient boundaries of a system when analyzing or designing it. If the boundary of a model is too wide it will be much harder to handle and analyze. On the other hand, if it is too narrow it can mislead and give an inaccurate model of the systems real behavior.

Thus, SD models are basically a computer-aided approach to present, analyze and design dynamic systems. It is a good methodology to use when modeling complex dynamic systems whether it is a economical, environmental or any other intra-connected system. SD models have been used for various systems in different domains and have been proven very helpful in previous implementations [49, 67].

Below are just a handful of applications that System Dynamics can be applied to.

Applications

- Economics
- Business
- Social Science
- Population Science
- Environmental Science
- Medical Science

In addition to the applications mentioned above there are many more fields where System Dynamics are put to good use. It is an expanding field of science and have been growing ever since Jay W. Forrester initially developed the field in the late 1950s[23].

To give an understanding of how SD models are structured and interpreted we will in the following sections discuss System Dynamics concepts and thinking.

B.1 The Concept of System Dynamics

A SD model can describe systems that includes:

- Interdependencies
- Mutual interaction
- Circular Causality
- Information Feedback
- System Delays

Most complex systems are likely to contain all of the above properties. Each property characterize the behavior of the system and influence the total outcome. The following sections describes how the properties are captured in the model.

B.1.1 Interdependence: Positive and Negative Influence

In a SD model the interdependence between two components is denoted with an arrow and a sign that explains how it influences the connected component. The influence and the sign can either be positive (+) or negative (-). Figure 27 clarifies the influence a change have depending on the type of sign.

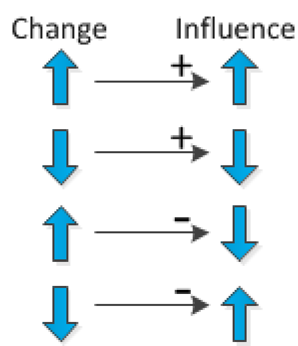

Figure 27: Change and Influence relation.

B.1.2 The Feedback concept

In System Dynamics the feedback is a core concept that is involved in most complex systems. A feedback loop exists in a system if a change travels through the system and at some time returns to its point of origin, hence the name. This can influence a system in two ways. It can reinforce the initial change and is then called a **positive feedback loop**. A loop that oppose the initial change is called a **balancing** or **negative feedback loop**. The causal relationship of the components in a feedback loop is presented in a causal loop diagram, displayed in Figure 28. It is called a causal feedback loop because it only consider how the components influence each other and not at which rate they increase or decrease.

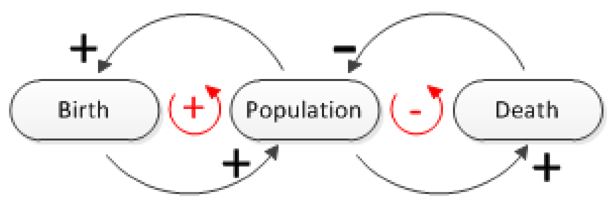

Figure 28: Causal loop diagram of population.

In Figure 28 there are two feedback loops, one positive displayed to the left and one negative displayed to the right. When labeling a loop with either positive or negative feedback (sometimes "R" for reinforcing and "B" for balancing) we define the polarity of the loop. A system with only a positive polarity will continue to grow with time until it probably collapse. A system with only a negative polarity have a tendency to generate a oscillating behavior. Most complex systems are composed through a mixture of positive and negative feedback loops. As in the example in figure 28 population is regulated through a reinforcing loop and a balancing loop. If the number of births increases it will of course increase the population which in turn will increase the number of births, thus reinforcing the loop. This loop alone would have an exponential growth. However the population is also affected by the number of deaths and the number of deaths is regulated by the population in turn.

If a feedback loop is have a long path it is still easy to determine the polarity of the loop. Just by multiplying the signs along the path will give the polarity of the feedback loop. One can keep in mind the following multiplication thumb rules when determining the polarity of feedback loops:

$$\begin{aligned} + \cdot + &= + \\ - \cdot - &= + \\ + \cdot - &= - \\ - \cdot + &= - \end{aligned}$$

As mentioned above the causal loop diagram does not reveal anything about in which grade the components affect one another. It provides an qualitative analysis, an insight of the structure and the behavior of the system. To achieve a more quantitative model we must include equations explaining the dependencies between components. How and in which grade components affect each other can be defined with linear or differential equations depending on the dependence characteristics.

B.1.3 Equations and Notations

The equations for the system for the population example can easily be explained.

The population level at time t is denoted $P(t)$.

The number of births is denoted B and the number of deaths is denoted D.

The birth rate is denoted b and is the number of births divided by the total number of the population: $b = \frac{B}{P}$

The death rate is denoted d and is the number of deaths divided by the total number of the population: $d = \frac{D}{P}$

With the above notations and equations we can calculate the quantity of the population for the next time step:

$$\begin{aligned} P(t+1) &= P(t) + B - D \\ &= P(t) + b \cdot P(t) - d \cdot P(t) \\ &= P(t)(1 + b - d) \end{aligned}$$

B.1.4 The Stock and Flow Concept

When dealing with levels of something in a dynamic system the approach is to use a Stock and Flow Concept. A Stock and Flow diagram (SFD) distinguish the causal relationship of levels, rates and constants which a causal diagram does not distinguish. The Idea is to define some of the components as stocks. These stocks contains a level of something and can increase or decrease depending on the flow in and out. An excellent example containing such stock with in and outflow is the population example mentioned in the previous section. The level of people is regulated through the number of births (the inflow) and the number of deaths (the outflow). The number of births and deaths are regulated through the birth and death rate respectively. The Stock and Flow representation of the population example is shown in Figure 29.

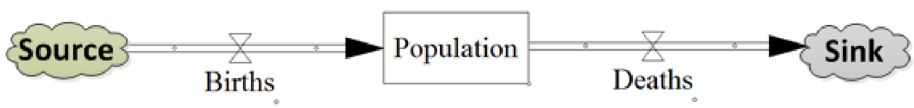

Figure 29: A SFD of population.

In Figure 29 the number of citizens i.e the population is represented by a rectangle which symbols a stock of people and the rates are represented by valve symbols.

There are two clouds in Figure 29 which represent the in and outflow. The first cloud represent an endless source of something that flows into the system, in this case people and the other cloud represent a sink where people vanish after death. thus, there is a endless flow from the source to the sink.

Figure 30 clarifies the relationships, loops and rates of the system. The constants are denoted with a name. In this example we consider the rates controlling births and deaths to be constant and have therefore no sign beside the arrows connected to the valves. Also the feedback loop is highlighted in the SFD below.

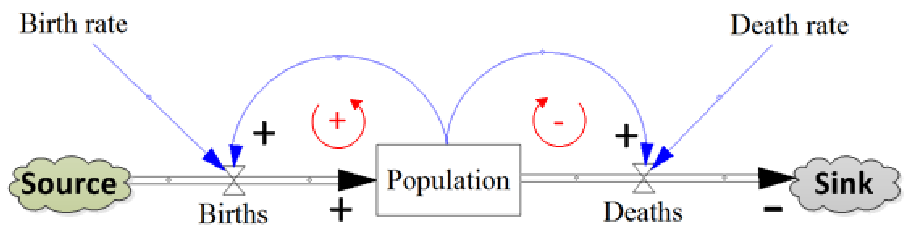

Figure 30: A detailed SFD of population.

B.1.5 System Delays

A problem that makes it difficult to model dynamic systems is that it can contain internal delays. The delays will cause the entire system to behave differently compared to the same system without delays. If a system contains delays it often means that there will be oscillations in the system. Imagine that in the real world it takes sometime for information to travel. For instance it will take a couple of days before a factory perceives an increased demand of their product and can increase the manufacturing speed. In the same way it will take a couple of days before the factory perceives an decreased demand of their product so they can slow down the manufacturing. This will cause the system to oscillate and affect the behavior of the entire system making it more difficult to model. In a SD model this is represented with two parallel lines on the linked arrow. Figure 31 clarifies the notation.

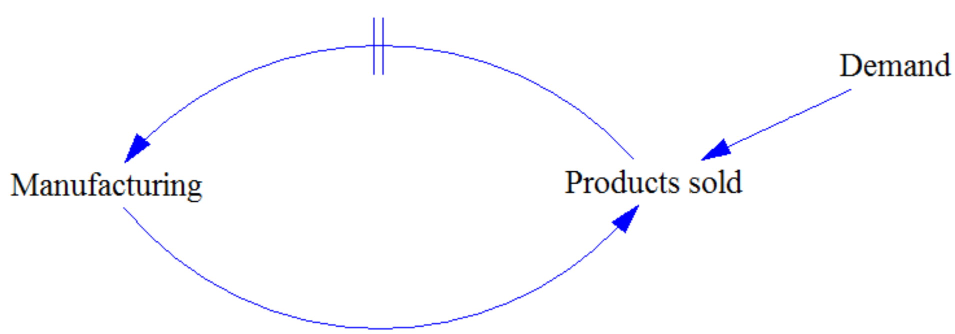

Figure 31: An example of a delay scenario.

B.2 A System Dynamics Approach

When developing a SD model one can follow the guide lines shown below. For a good result this should be done together with experts in the field in question.

1. Define the situation, the problems and a boundary of the system with a dynamic aspect, i.e how the internal components affect each other.
2. Identify Interdependencies in the system.
3. Identify the most important stocks and flows that regulates these stocks.
4. Identify the source that influence the flows and how it affects the system.
5. Identify feedback loops.
6. Use a graphical approach to draw a causal loop diagram over the system that links all the interdependencies and clarifies feedback loops and delays.
7. Determine the equations explaining the relationship between components.

When a complete model have been developed and is going to be used for simulation one must first estimate initial values for the components. This can be done through real world data acquisition, market research or through speculations based on expert opinions.

C Abbreviations

Abbreviation	Meaning	page
AI	Artificial Intelligence	7, 14
SD	System Dynamics	7, 17, 32
WBAN	Wireless Body Area Network	7, 22, 24, 25
HRI	Human-Robot-Interaction	7, 14
HMM	Hidden Markov Models	8, 41
SA	Situation Awareness	14
SMM	Shared Mental Models	14
HR	Heart Rate	20
HRV	Heart Rate Variability	20, 42
GSR	Galvanic Skin Response	20, 25
ST	Skin Temperature	20
FT	Finger Temperature	20
PD	Pupil Diameter	20
BVP	Blood Volume Pressure	20
RR	R wave to R wave interva	20
ECG	Electrocardiogram	20, 25
EMG	Electromyogram	20
EEG	Electroencephalogram	20
PDA	Personal Digital Assistant	22
RCP	Rich Client Platform	9
GUI	Graphical User Interface	9
XML	eXtensible Markup Language	9
GPS	Global Positioning System	25
GIS	Geographic information system	27
ARFF	Attribute-Relation File Format	31, 40
ASCII	American Standard Code for Information Interchange	31
SDF	Stock and Flow Diagram	77, 78