Aalborg University

Semester project

Real-Time Trust Assessment Based on Motion Data for Safe Human-Robot Collaboration

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Autumn semester 2022.

Dec 21th 2022

AALBORG UNIVERSITY
STUDENT REPORT

Aalborg University
Department of Materials and Production
Department of Architecture, Design and Media Technology
http://www.mp.aau.dk

Title:

Real-Time Trust Assessment Based on Motion Data for Safe Human-Robot Collaboration

Theme:

Trust assessment

Project period:

Autumn semester 2022.

Project group:

Participant:

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Number of pages: ??

Date of completion:

Dec 21th 2022

Abstract

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Preface

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Ozren Vučićević

1 Introduction

As the field of robotics is developing, robotic systems are getting more automated and collaboration in close proximity with humans is increasing. Introduction of robots improved a lot of areas in our every day life. Science, engineering, medicine and a lot of other areas including the social aspects have rapidly improved with this collaboration and the connection between humans and robots will continue to grow. This development is bringing its own set of challenges and problems.

There is a vast range of applications regarding the robotic systems which include tasks such as package delivery, entertainment industry, disaster search and rescue, service, and manual support for physical tasks. Especially in engineering industry, which is the focus of this report, it is common to see humans collaborating with robots on a day-to-day basis, working together on tasks or in close proximity to each other. Many companies have big industrial robots which, if not careful, have the possibility to be dangerous to humans. This brings up the question: "Should humans trust robots?"

This is a complicated statement because, it is hard to look at machines as a agent that can or can not be trusted. Questions similar to this were a big topic of science-fiction and academia long before robotics got as advanced and developed like in today's society. In 1941, author Isaac Asimov wrote a science fiction novel "I, Robot", where he stated the Three Laws of Robotics (Wikipedia 2022b):

1. A robot may not injure a human being or, through inaction, allow a human being to come to harm.
2. A robot must obey the orders given it by human beings except where such orders would conflict with the First Law.
3. A robot must protect its own existence as long as such protection does not conflict with the First or Second Law.

Even if these laws are a part of science-fiction novel, they can provide an insight in the way engineers and researchers view the relationship of the human-robot collaboration. Safety is the most important factor when doing collaborative tasks and after that condition is satisfied, other aspects like productivity can be explored and improved. Human-robot interaction is not a new area of research, but only recently a lot of papers started being published.

In an effort to explore area of human-robot interaction, Aalborg University's HRI department is working on a European Commission project within Horizon 2020 Framework Program called "DrapeBot". The idea of this project will be to improve collaborative draping of carbon fiber parts. Draping carbon fiber on complex geometry is currently done by humans, so the robots will collaborate by helping to hold and carry the carbon plates, while the humans will drape them in to desired shape. (HORIZON2020 2022)

1.1 Human-Robot Interaction (HRI)

Study between interactions of humans and robots is called human-robot interaction, also referred by researchers as HRI. This is a multidisciplinary field of science that has contributions from artificial intelligence, human-computer interaction, robotics, design, psychology and natural-language understanding. (Wikipedia 2022a)

As a broad division HRI can be divided in four areas of application (Sheridan 2016):

1. Human supervisory control of robots in performance of routine tasks.
2. Remote control of robots in airborne, terrestrial , undersea and space vehicles for tasks in different hard-to-access environments.
3. Automated vehicles that have a human as a passenger.
4. Human–robot social interaction.

This report focuses on the 1. division. In an industrial environment there is a large variety of robots doing different assembly line task like welding, pick and place operations, painting etc. Humans working with industrial robots have supervisory tasks or they work in collaboration with them.

A good example is the Baxter assembly line robot, shown in Figure 1.1, which is a product made in Boston by Rethink Robotics. It is designed with intention on operating in close proximity with workers, while regarding their safety. It is designed to be mechanically compliant, like the human body. One of interesting innovations are the eyes of Baxter robot which do not allow robot to see, but have u purpose to communicate with the operator on what the robot is currently doing. Also, the arms of the robot are mechanically compliant, which enables the operator to move its hands and teach it manipulation task or to work in close proximity to one another.

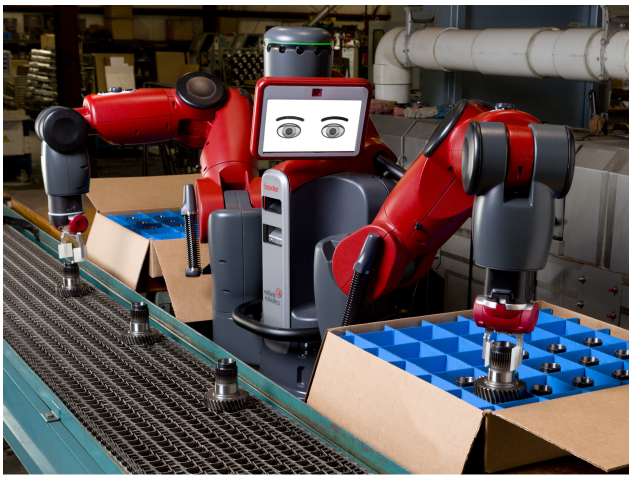

Figure 1.1: *Baxter robot*

Human–robot interaction (HRI) is a growing and rapidly expanding field which will require greater involvement of design and research. To date, human factor involvement in to human-robot research is limited and in the future it will be needed more then ever. As the human race is evolving at a slow pace, unlike robots, a need for specific conclusions about HRI will become invalid in the future.

1.1.1 Human-Robot Collaboration (HRC)

Human-robot collaboration (HRC) was briefly introduced in the last chapter on the example of the Baxter robot. Psychology, adaptation and learning process issues can happen in human-robot collaboration where the human needs to adapt to the industrial environment. Work-space that includes robots can cause a negative response by the humans, who can perceive them as dangerous and outrageous. (Kadir Alpaslan Demira 2017) Human behaviour can be used as a source of information for the robot to produce a response in terms of reducing the cycle time and waiting time. (Chiuhsiang Joe Lin 2022) Parameters like movement, muscle activity, visual cues and brain signals can signalise human intention in the collaborative tasks, to improve the interaction. It is clear that in the real-world scenarios, understanding human intention and behaviour with cues like this will be a difficult problem to solve, because of the uncertainty and vagueness of humans.

As mentioned before, that negative response to a robot in the work-space can have an impact on the safety perception by the workers. This can influence the trust level, comfort, ability to predict and control the situation and experience of the worker. (Chiuhsiang Joe Lin 2022) As an example, as mentioned in (T.Arai 2010), robot moving toward a human in higher speeds will increase the safety concerns by the human and he will find difficult to predict the robot's movements. This provides an insight in to the importance of the human emotional status when doing collaborative tasks with the robot. This psychological status is important for maintaining performance on an optimal level.

1.2 Trust

Trust, as referred by the Oxford English Dictionary is a "firm belief in the reliability, truth, or ability of someone or something" or the "confident expectation of something." COBUILD Advanced English Dictionary by Collins also refers to a "firm belief or confidence in the honesty, integrity, reliability, justice, etc. of another person or a thing."

In common usage, trust is the expectation that something good will happen, while also having the knowledge that it might not. It is mostly considered a human concept, because in most cases only a person can decide what constitutes something trustworthy or not. There are different ideas of trust and we can divide them in to the idea of "Performance trust" and "Moral trust". Performance trust is referring to the belief that the trustee is capable of task completion, while moral trust refers to the trustor's confidence that the trustee is choosing the right action morally. When referring to robots, performance trust is the first idea that comes to mind as something that can be measurable.

This paper focuses on the human-robot trust relationship. (Chang S.Nam 2021)

1.2.1 Human-Robot Trust Relationship

The work in this field is focused on the reliability and ability characteristics of robotic systems. One of the examples of that is a meta analysis of factors that prior research identified as the most relevant points that dictate trust in human-robot interactions. (Peter A. Hancock 2011)

After collecting data from 21 studies, the researches found out that factors related to the robot—specifically, its performance and consistency, were the biggest association with trust. Applying human factors (e.g., comfort, attitudes, happiness) and environmental factors had the smaller contribution. A person can gain or lose trust in the robot, without looking the robot as a moral agent.

The problem with human-robot trust comes when you try to measure it. When looking to human-human relationships trust is often signified by one or more moral characteristics (e.g., benevolence, integrity, sincerity) and performance characteristics (reliability, ability). Regarding that point, a distinction has been made in (Theresa Law 2020) to separate trust into "relation-based" trust and "performance-based" trust. Performance-based trust revolves around the idea that the robot is trusted to be capable, competent and reliable to do its task, without the need of supervision or monitoring. Performance-based trust can also depend on the robot's predictability, responsiveness and transparency. On the other hand, relation-based trust revolves on the idea of participant trusting the robot to be a part of the society and not as a part of the factory doing a job, with no regard or knowledge of social norms. When comparing these two, relation-based trust is given to robots who would function good in human-robot interaction, for example as children toys and parts of the every day life, and performance-based trust would be given to factory robots who are doing a precise task. Usually, robots that have performance-based trust are barred of from human interaction. Currently there is not a lot of ways to measure trust between humans and robots, but there are some standardised questionnaires that can be used as trust indicators. One of them was used in this report.

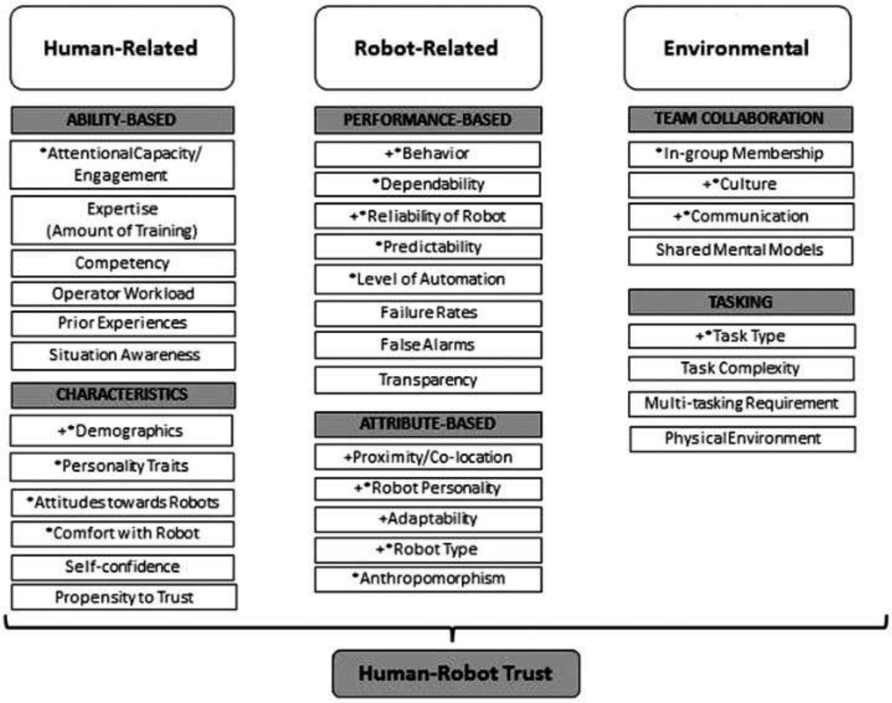

Figure 1.2: *Factors of trust development in human-robot interaction (Peter A. Hancock 2011)*

1.2.2 Objective Measure of Trust

In experiments, the primary means of measuring the participant's trust in a robot are the subjective questionnaires. Lot of studies use this subjective questionnaires and rely on them to validate their trust measurements, others create their own. There are validated questionnaires and non-validated ones, which are usually made by the study itself. In general, this subjective measurement methods are used more often then objective ones. Objective measures allow the researchers to analyze actually robot interaction, instead of relying on subjects speculation about themselves (e.g., reason, motivation, beliefs, etc.) Since trust in automation was used mainly for evaluation purposes, most of the methods for trust assessment are based on the subjective questionnaires mentioned before. Also, when there is a need to measure trust in real time, it is not practical to have constant trust questions answered by the humans. Because of this, new methods of trust estimation are needed to be tested. Unlike subjective psychological indicators of trust, there is a possibility that trust can also be measured by some physical indicators. Some of those indicators can be human movement or hearth rate. This report is exploring the possibility of trust indicators in humans based on their movement. To achieve that, a study called Laban Movement Analysis is used to extract the different movement descriptors, which can be used to further analyse the behaviours based on the movement data. (Caroline Larboulette 2016)

1.3 Machine Learning With Human Movement Data

As the machine learning and artificial intelligence (AI) algorithms are rapidly improving, they are being used in a lot of different sectors, private and public, to make basic and complex decision-making processes more simple. Computers are a good way to analyse and work with large data-sets. They have simplified extracting insights from data that would make less sense for a human to analyse. In toady's society, algorithms like this are using large amounts of data to influence peoples lives in a variety of areas, from adds on the internet or assisting banks with creditworthiness of its members. (Lee 2021)

In supervised machine learning, algorithms are trained with "labelled" training data, and on basis of that data they will predict the output. The labelled data is input data that is already tagged with a correct output. In this situation, this training data that is placed in to the algorithm works as the supervisor, that will teach the machine to predict the correct output. We can relate that to a student that learns with the supervision of the teacher. Often this algorithms depend on large amount of data sets, or training data. (Lee N. T. 2019)

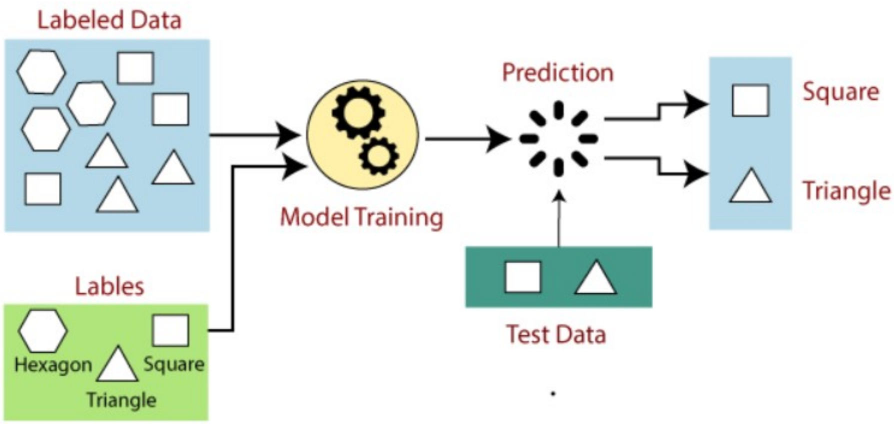

Figure 1.3: *Supervised machine learning (JavaTpoint 2022)*

There are several ways to record human movement. The usual methods are using cameras or motion-tracking devices which are placed on the body of the test subject. Both methods usually create big data-sets for further analysis. A good example of research like this is a study, shown in (Yoshikawa 2020), about the motion data analysis by supervised machine learning algorithms. This research was intended to developer technology which will assist robots to adapt to human behaviour patterns in real-time to maximize the system efficiency, understand human behaviour and movement, and show effects in ergonomics and assist robotics. Motion trackers were placed on the participants to gather motion-data, which was used to train classification machine learning models. As explained in the article, this kind of approach to tasks related to analysis of the human movement and behaviour is most common, because a large amounts of labeled examples are created by recording movement.

2 Problem Analysis

In today's industry, big industrial robots that can cause harm to humans are kept in cages with safeguards so injuries can be avoided. In the future, the hope is that human operators will trust the robots enough to work with them in close proximity on collaborative tasks, while also providing the safety in their interaction by the robots. Trust between humans and robots, as mentioned in Section 1.2.1, affects productivity and speed of finishing tasks, so in collaboration having a good model for indication of trust can be beneficial for overall performance.

To enable close-proximity human-robot collaboration (HRC), part of the focus has to be put on the trust relationship between the human and the robot. In this paper that trust relationship is explored and measured to approximate the appropriate levels of trust in the operator toward the robot, because that level will influence the behaviour of the operator in terms of performance and proximity to the robot. As mentioned in Section 1.2.1, a division has been made in two forms of trust, relation-based trust and performance-based trust. Relation-based trust is becoming increasingly important in toady's society and it will be important to understand it better, but this paper will focus more on the performance aspects of trust.

As mentioned in Section 1, Aalborg University is working on a European Commission project. To replicate the environment of collaborative draping of carbon fiber, a series of experiments has been conducted by Aalborg University's HRI department, with a purpose to gather movement data which will be analysed.

2.1 Problem Description

The "DrapeBot" project (HORIZON2020 2022) revolves around collaborative draping of carbon-fiber between humans and robots. Draping of composites is a procedure where thin layers of composite material, in this case woven carbon-fiber, are stacked on top of each other to fit a chosen geometrical structure. When possible, this procedure can be automated and no human involvement is needed. As explained in (Abdelhakim Cherouat 2005), for more complicated shapes, this process is often done manually by workers. Because of that, the price of production increases with additional labour costs. To increase the productivity and speed, a collaborative work that includes a robot and a worker would fit this scenario. Also, when working with composite plates that are heavy and hard to handle, a robot will have to transport them in the facility. The whole process would include the robot, who would carry and hold the carbon-fiber sheets, and a worker that would drape them around a specific geometry.

Figure 2.1: *Draping of composites*

Aalborg University's HRI department conducted a series of experiments to emulate the carbon-fiber draping and gather data. Data was gathered by the Xsens MVN Awubda tracking suit and trust questioners from (Schaefer 2016), which will be used to test the hypothesis of the project. The hypothesis focuses on the idea that the performance-based measurements of the humans trust towards the robot and human movement patterns are able to be a good indicator of trust levels towards the robot, which will be used for identifying critical points of the human-robot interaction. The belief is that some of the unintentional body movements and patterns of movement of the human in the interaction can be used to approximate the trust level and determine when the trust level is inefficient or dangerous. Trust level can ether be to high which is dangerous. In this case, that would mean that the human would be too comfortable working with the robot and endangered his safety by standing in to close proximity. If the trust level would be inefficient, that would mean that the human would not trust the robot, so as mentioned in Section 1.2.1, performance and efficiency of completing the collaborative task would be lowered. It is also important to note, that the trust relationship will be changing as the interaction is happening. The trust levels at the beginning of the experiments will evolve depending on the different parameters of the interaction. That is why, it is important to have the data segmented in time, in relation to the task that is happening. In the future, this trust relationship would be evaluated in real time and the robot actions would be corrected appropriately.

Figure 2.2 shows how assessment of trust with trust calculations and motion data can be used to calibrate trust, by communicating the operator or by changing the robot behaviour.

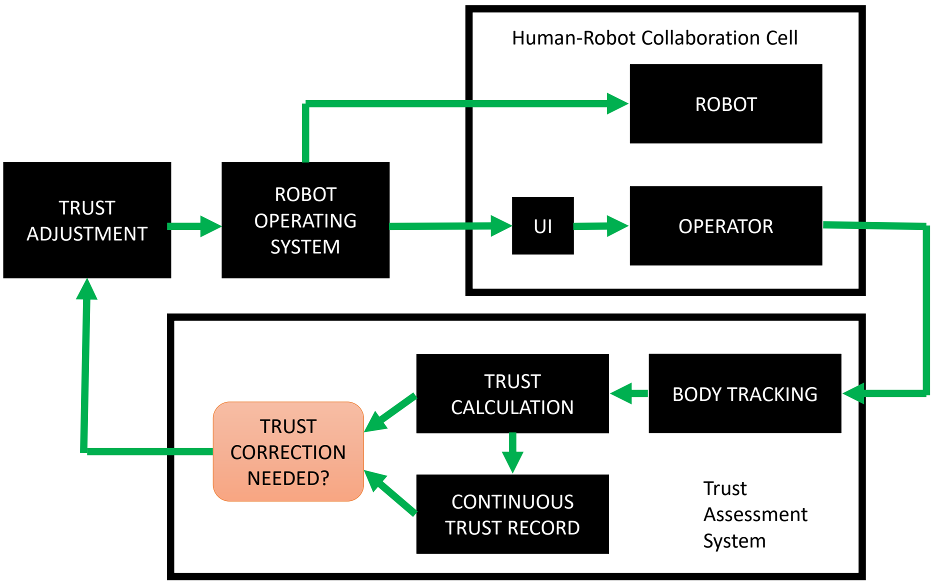

Figure 2.2: *Trust assessment system involving a human-robot collaboration cell*

In the "DrapeBot" HORIZON2020 project Human-Robot collaboration cell would contain a worker and robot doing a collaborative close-proximity draping task, in witch motion data, or different body data, from the worker would be collected, with which the trust calculation would be conducted. If there would be a need for trust adjustment, either the robot would change its pattern of behaviour or the operator would be notified by the user interface that he needs to correct his behaviour. This would resoult in a safer, more productive and efficient system of close-proximity collaboration of draping between the worker and the robot.

2.2 Problem Statement

3 Experiment

One of the main ideas of this project is carbon-fiber draping. Draping of composites is a procedure where thin layers of composite material, in this case woven carbon-fiber, are stacked on top of each other to fit a chosen geometrical structure. As explained in (Abdelhakim Cherouat 2005), for more complicated shapes, this process is often done manually by workers. This can also be seen on Figure 2.1. Because of that, the price of production increases with additional labour costs. To increase the productivity and speed, a collaborative work that includes a robot and a worker would fit this scenario. The robot would bring the carbon-fiber sheets, while the worker would drape them.

To emulate this process AAU HRI department made a series of experiments as mentioned in Section 2.1. When trying to replicate the HORIZON2020 project idea, there were requirements that needed to be accomplished by the experiments. HRI department decided to emulate the collaborative task of transferring the carbon plates from one place to another and the task of draping in separate experiments.

For gathering the data, 20 participants were involved in two experiments, as shown in the Table 3.1:

A) Transport task (20)

B) Draping task (20)

Table 3.1 shows participants, with numbers from 1-20. Both experiments contained a big industrial robotic arm (KUKA 300 R2500), shown in Figure 3.1 and one test subject per experiment. Good thing about using a robot this size is the possibility of participants having less trust in the robot trough the encounter, even if the experiment was safe and no harm would happen to participants. This makes the experiment more realistic. Instead of carbon-fiber plates, robot and participants were carrying and draping textile material.

Figure 3.1: *KUKA 300 R2500*

3.1 Transport Task

Experiment A was the task of transport. The goal was to replicate the close-proximity task of transporting the carbon-fiber plates from one point to the other. As mentioned in Section 3, textile material was used in the experiment. One part of textile was connected to the robot arm's gripper, and the other was handled by the participant. In the experiment the textile was transferred from one table to another, while the participant was walking alongside the robot between the tables. The distance between them was the length of the textile sheet.

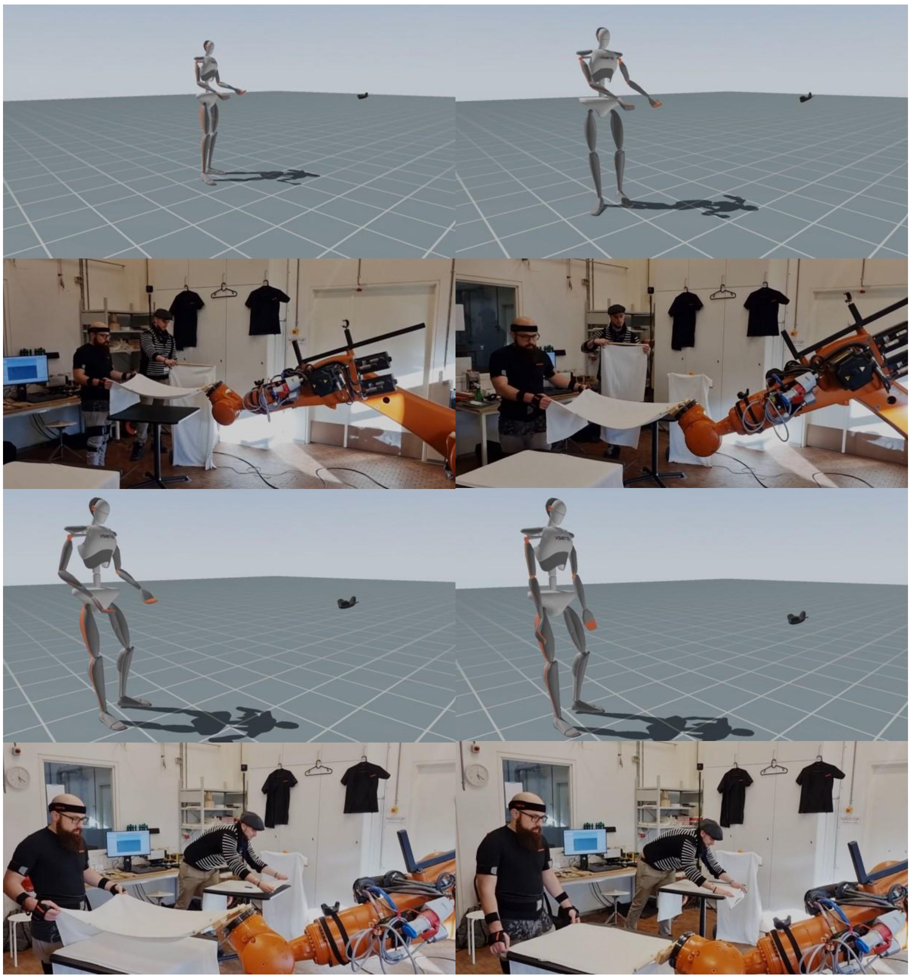

Figure 3.2: *Collaborative transport task*

Figure 3.2 shows the experiment conducted, with the images from the motion tracking program used.

3.2 Draping Task

Experiment B was the task of draping. The goal was to replicate the close-proximity task of draping the carbon-fiber plates over the complex geometry by the worker. To emulate this the textile material used in the experiment is placed on the table by the robot, while the participant waits. After the robot places the material, the participant approaches the table and drapes the textile material over the table in close proximity to the robot, and backs away. After that the robot returns to its original position and the task is repeated. When applied in the industrial context, this requires that the worker is comfortable with getting in to close proximity to the robot when it is stationary in order to avoid lost efficiency and stress. Images from the experiment and from the motion tracking software can be seen in Figure 3.3.

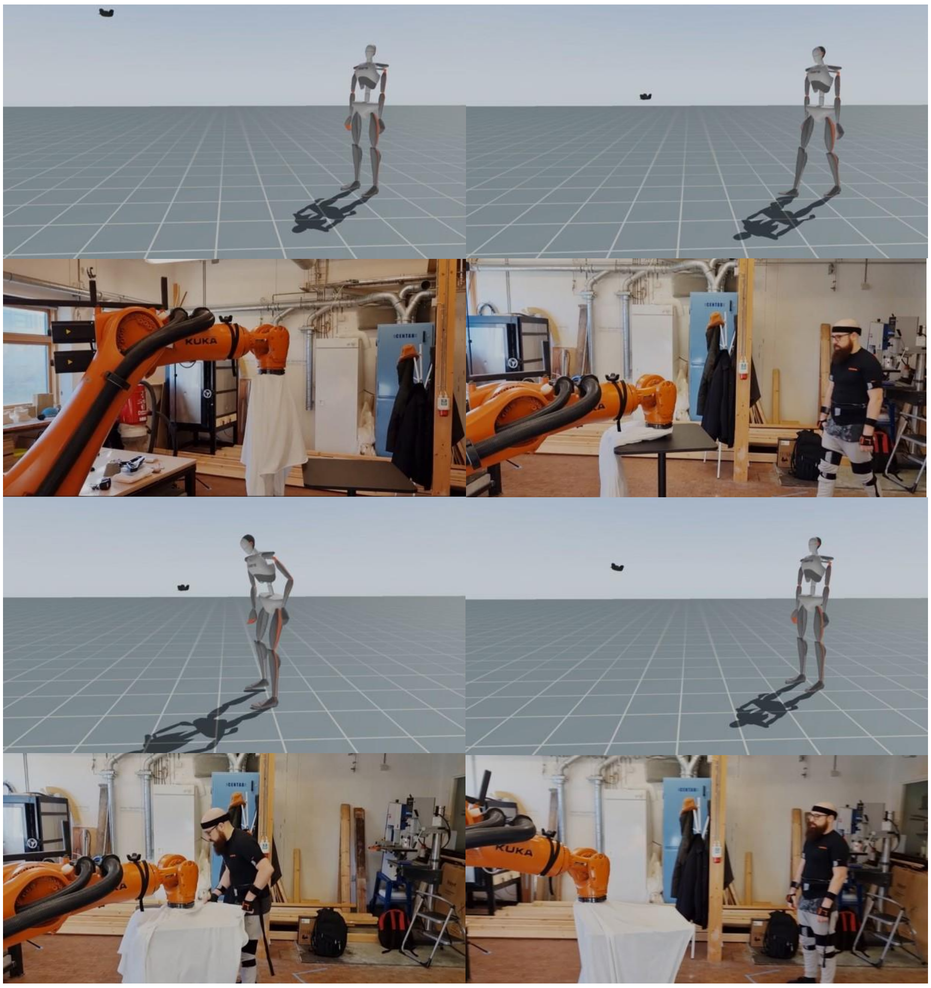

Figure 3.3: *Collaborative draping task*

3.3 Data Collection Procedure

The idea of data collection was to collect body movement data of the robot and the participants with the trust data collected from the questioners. Since this is a preliminary experiment, the only thing with the robot movement that was varying trough the experiment was the speed of movement, which can be seen in Table 3.1. Some participants would preform tasks with the higher robot speeds, and some with lower. Every task experiment lasted for approximately 10 minutes, in which participants would repeat the same task multiple times. After finishing the draping or transport task, participants would fill out a 14-question questionnaire regarding the trust in the robot, to provide a crude trust estimation. This means that every participants did 3 trust questionnaires, one before the first task, after the first task and the last after the second task.

Subject	First Task	Transport Speed	Age	Gender	DominantHand	Height
1	Transport	Slow	20	Male	Left	1.78
2	Draping	Slow	23	Male	Right	1.82
3	Transport	Fast	20	Male	Right	1.9
4	Draping	Fast	27	Male	Right	1.89
5	Transport	Slow	29	Male	Right	1.65
6	Draping	Slow	24	Male	Right	1.7
7	Transport	Fast	24	Female	Right	1.64
8	Draping	Fast	21	Female	Right	1.61
9	Transport	Slow	25	Male	Right	1.85
10	Draping	Slow	22	Female	Right	1.67
11	Transport	Fast	22	Female	Left	1.53
12	Draping	Fast	26	Male	Right	1.86
13	Transport	Slow	36	Female	Right	1.72
14	Draping	Slow	21	Male	Right	1.87
15	Transport	Fast	24	Male	Right	1.72
16	Draping	Fast	25	Female	Left	1.58
17	Transport	Slow	30	Female	Right	1.59
18	Draping	Slow	26	Male	Right	1.82
19	Transport	Fast	32	Male	Right	1.82
20	Draping	Fast	26	Male	Right	1.7

Table 3.1: *Experiment participants*

During the experiment, the participants were always at maximum distance from the robot, so there was no risk of injury, but it is presumed that the participants without prior robotic knowledge do not know the safety aspects of the experiment. In reality it is hard to replicate a real work environment between a worker and a industrial robot, so creating experiments like this are best ways of obtaining all of the needed data until testing on the real "DrapeBot" collaboration cell will be available.

3.4 Motion Tracking

Figure 3.4: *XSens MVN suit has 17 inertial and magnetic sensor modules. It is wireless so data is transmitted to the computer where the processing is visualised and performed*

For all of the experiments, motion tracking software was done using the XSens MVN Awinda tracking suit, shown in Figure 3.4. This is a wireless full-body motion capture system which consists of a tight-fitting shirt, gloves, a headband and a series of straps, which are used to attach 17 IMUs to the participant. An Inertial Measurement Unit (IMU) is a device that can measure and report specific gravity and angular rate of an object to which it is attached (Vectornav 2022). An IMU usally consists of:

- Gyroscopes: they provide a measure of angular rate
- Accelerometers: they provide a measure of specific force/acceleration
- Magnetometers: they provide a measurement of the magnetic field surrounding the system

For result accuracy, the participants body dimensions were measured before the tracking session. This measurements included height, foot length, shoulder height, shoulder width, elbow span, wrist span, arm span, hip height, hip width, knee height and ankle height. This information is needed for the system to separate the body in to different segments and joints. The XSens MVN Awinda system uses inverse kinematics to track the movements at a constant rate of 60 Hz, between the segments and joints of the body. The body segments and joints are not all connected to a specific sensor, but are rather calculated with the software and body dimensions. For this project it is important to note that there are 23 body segments. Segments are head, neck, four vertebra, left and right shoulders, upper arms, forearms, hands, upper legs, lower legs, feet, toes and the pelvis.

3.5 Trust Assessment

As mentioned in 1.2.2, in this types of experiments the most common way to get a trust measurement is with a trust questionnaire. In this experiment, a post-interaction questionnaire like that was also used. It was developed by Kristin Schaefer, as seen in (Schaefer 2016), where the final trust score is measured based on a series of questions regarding the participants view of the interaction between the robot. Questions were meant to measure the robot's predictability, capability, error rates and more. Even tough this questionnaire consists of 40 questions, there is a 14 question version that was made for environments where the results need to be found quickly between repetitive tasks. The trade of that is a loss in granularity of the results. The final trust scores are measured on a scale from 0 to 100, where the participant's agreements to statements suggest trust in the robot and get a positive scale and statements that suggest error expectations get a negative score.

4 Methods

To analyse the data, different methods will be used in the report and described in this chapter. Firstly, methods that were needed to describe the captured human motion data are explained and afterwards methods for correlating the data with the trust scores are explained.

As a starting point, before any segmentation based on proposed methods was done, the first crude movement separation was done by analysis of the repetitive movement by treating it as a signal. This will describe movement in relation to the task that is happening in the experiment with segments that were discussed and agreed upon after the experiment. This will simplify the classification later on in the project.

After that, it was important to capture human movement patterns or signals that could indicate a correlation with the overall trust of the participant towards the robot. The experiment captured movement of all parts of the human body. This was possible with the Xsense MVN Awinda as mentioned in Section 3.4. For the purpose of defining the captured movement data, Laban Movement Analysis was used.

During the analysis of the movement, a Principal Component Analysis (PCA) was used as a dimensionality reduction tool.

After the movement data was analysed and defined by the movement analysis, the idea was to find correlations between the movement and the trust of the participant towards the robot. For analysing big data sets, as was required in this project, machine learning classification algorithms are a good way to do that, as mentioned in Section 1.3.

4.1 Related Work in Movement Analysis

When looking into movement segmentation methods, many are based on changes in the low-level kinematic features. For example (Fod A. 2002) segments the movement in two different ways that utilize angular velocity of 4 different degrees of freedom in the arm. (Zhao L. 2005) is calculating boundaries where the hand linear acceleration and curvature are above some threshold. As can be seen, this papers are using low-level features, like acceleration, velocity and curvature of the body segments as markers for segmentation of movement. These kinematic methods are extremely efficient, but they produce simple segmentation.

There are more sophisticated motion capture segmentation methods, which produce a more high-level segmentation then the kinematics methods mentioned. They use data analysis with time series data by creating time clusters related to different motions. One of examples is shown in (Barbic J. 2004), where two different segmentation methods are implemented based on data compression. First method segments the data based on Principal Component Analysis (PCA), where the projection error increases on incrementally larger segments of motion capture data. The second method segments the data by spotting the changes in the distance of fitting a small segments of motion data to a Gaussian distribution model of the frames that precede the segment.

Some work has also introduced Supervised machine learning as a way of segmenting the data. As an example (Kahol K. 2004) uses a Bayesian classifier as a mean to derive choreographer segmentation profiles regarding the dance motion capture sequences. It is important to note, that to use methods like this on a general motion examples is extremely difficult and the amounts of data needed for general Supervised learning model of movement would be enormous. However, when using it for specific movements like dance motion it can be useful.

4.2 Laban Movement Analysis

Human motion is a field of study that is becoming increasingly active and includes motion analysis, motion recognition and motion synthesis. Capturing human motion and analysing it can be beneficial for a wide variety of applications. Most notable ones are film and game industry, human-computer interaction and ergonomics. Recently data related to motion capture is becoming free and available, which helps the study of movement. The problem with this data is that it rarely portrays the expressiveness of the human, which can indicate their state of mind, intent and emotion.

Laban movement analysis (LMA), also referred as Laban/Bartenieff movement analysis, is a method and language used for interpreting, describing, visualizing and documenting human movement. LMA has its roots in the work of Rudolf Laban, which was later extended by Irmgard Bartenieff, Lisa Ullmann and others. (Caroline Larboulette 2016) It is based on different fields of research, like kinesiology, psychology and anatomy, and it has a vast area of usage. It is used by actors, musicians, dancers, health professionals, psychotherapists and others.

Other learning based methods of human motion segmentation have the ability to separate motion semantically. This is useful for specific class of motions, like dance moves or sign language, but when looking into general motion capture data, they wont be feasible. (Catherine Pelachaud 2007) When looking for a classifier for general motion, it has to have classes for all motions, which are significant in meaning and practical to use for classification. That is where LMA excels.

LMA is used to identify components that can describe the structural, geometric and dynamic properties of human motion. This analysis has four components:

- Body
- Space
- Shape
- Effort

Body, Shape, and Space are used to define what type of motion is performed, while the Effort describes how a motion is performed. Body and Space are used to describe how the human moves withing the 3D space or in relation with the body. The Effort relates to the intention of the movement and focuses on aspects of movement like dynamics and energy. Effort is composed of four different values.ž

Next two sections will explain what are the movement descriptors of the Laban Movement Analysis, that can be seen in the Table 4.1. Descriptors from this table, as well as the low-level and high-level division of the descriptors is proposed by (Caroline Larboulette 2016).

Low-Level	High-Level
Kinematic / Dynamic Descriptors	Body Descriptors
Duration *Velocity* *Acceleration* *Jerk* *Curvature* *Quantity of movement*	*Action presence* *Center of mass displacement* *Balance* *Support*
Geometric Descriptors	Space Descriptors
Bounding box *Bounding sphere* *Bounding ellipsoid* *Convex hull* *Displacement* *Rotation* *Center of mass*	*Distance covered* *Area covered* *Hip height*
Effort Descriptors	Shape Descriptors
Weight effort *Time effort* *Space effort* *Flow effort*	*Bounding Volume* *Shape direction* *Shaping* *Extensiveness* *Arm shape* *Elbow shape* *Shoulder angle* *Hands relationship* *Feet relationship*

Table 4.1: *Laban Movement Analysis movement descriptors.*

4.2.1 Motion Representation

We can describe movement as a sequence of joint configurations of the skeleton in a selected period of time. For this project, each joint configuration at the time t_i can be described by:

- A set of m joint/segment positions: $\mathbf{x}(\mathbf{t_i}) = \{\mathbf{x^1}, \mathbf{x^2}, ..., \mathbf{x^m}\}(\mathbf{t_i})$ where $\mathbf{x^k}$ are the relative positions associated to the k_{th} joint with $1 \leq k \leq m$;
- A set of m joint angles: $\mathbf{x}(\mathbf{t_i}) = \{\mathbf{q^1}, \mathbf{q^2}, ..., \mathbf{q^m}\}(\mathbf{t_i})$ where $\mathbf{q^k}$ are the relative rotations associated to the k_{th} joint with $1 \leq k \leq m$;

Every position $\mathbf{x}(\mathbf{t_i})$ is described by $\mathbf{3} \times \mathbf{m}$ dimensional vector for representing the position, or a $\mathbf{4} \times \mathbf{m}$ dimensional vector for representing the quaternionic rotation.

4.2.2 Low-Level Motion Descriptors

Low-level motion descriptors are described as kinematic or dynamic quantities that can be derived directly from the movement representation, or geometric descriptors that describe the skeleton configuration at a given point/points.

Kinematic Descriptors

As seen in the Table 4.1, they are properties of motion like duration of movement, velocity, acceleration, jerk, curvature and quantity of movement.

In the report, bold characters will describe scalar values of quantites (norm).

- **Duration**: describes the length of movement
- **Velocity**: describes velocity for one joint (rate of movement)

$$v^k(t_i) = \frac{x^k(t_{i+1}) - x^k(t_{i-1})}{2\delta t} \tag{4.1}$$

  And its scalar value

$$\mathbf{v^k(t_i)} = \sqrt{v_x^k(t_i)^2 + v_y^k(t_i)^2 + v_z^k(t_i)^2} \tag{4.2}$$

- **Acceleration**: describes velocity for one joint (rate of change of velocity)

$$a^k(t_i) = \frac{x^k(t_{i+1}) - 2x^k(t_i) + x^k(t_{i-1})}{\delta t^2} \tag{4.3}$$

  And its scalar value

$$\mathbf{a^k(t_i)} = \sqrt{a_x^k(t_i)^2 + a_y^k(t_i)^2 + a_z^k(t_i)^2} \tag{4.4}$$

- **Jerk**: describes motion smoothness (rate of change of acceleration)

$$j^k(t_i) = \frac{x^k(t_{i+2}) - 2x^k(t_{i+1}) + 2x^k(t_{i-1}) - x^k(t_{i-2})}{2\delta t^3} \tag{4.5}$$

  And its scalar value

$$\mathbf{j^k(t_i)} = \sqrt{j_x^k(t_i)^2 + j_y^k(t_i)^2 + j_z^k(t_i)^2} \tag{4.6}$$

- **Curvature**: describes the speed of curve change from a given point. It can be computed as the cross product of acceleration and velocity

$$C^k(t_i) = \frac{||a^k(t_i) \times v^k(t_i)||}{v^k(t_i)^3} \tag{4.7}$$

  And the curvature radius

$$R^k(t_i) = \frac{1}{C^k(t_i)} \tag{4.8}$$

- **Quantity of Motion (QOM)**: describes the weighted average of the velocities of body parts

$$qom(t_i) = \frac{\sum_{k \epsilon K} w_k v^k(t_i)}{\sum_{k \epsilon K} w_k} \tag{4.9}$$

Geometric Descriptors

This descriptors describe geometrical characteristics of the body, relating the body to itself or to the environment. Bounding shapes shown in Figure 4.1 are a good example of geometric descriptors. Geometric descriptors include bounding box, bounding sphere, bounding ellipsoid, convex hull, displacement, rotation and center of mass.

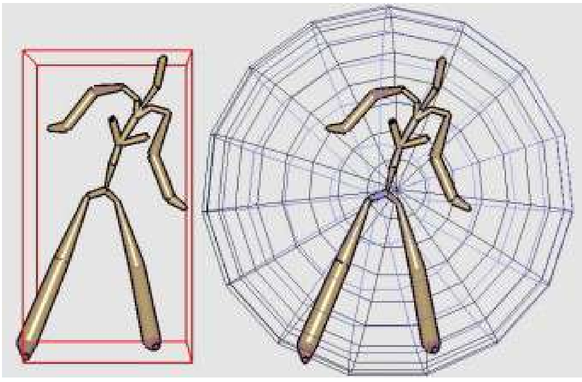

Figure 4.1: *Bounding shapes: Bounding box(left), Bounding sphere(right) (Caroline Larboulette 2016)*

- **Bounding Box**: describes the box(rectangular parallelepiped) that surrounds the body in 3D (-x, +x, -y, +y, -z, +z)
- **Bounding Sphere**: describes the bounding sphere (center and radius) that surrounds the body in 3D
- **Bounding Ellipsoid**: describes the bounding ellipsoid (center, r_a, r_b, r_c) that surrounds the body in 3D. It is more accurate then the sphere which gives a better volume approximation, but is harder to compute
- **Convex Hull**: describes the convex hull(smallest convex set that contains all joints) that surrounds the body in 3D. It gives a better representation of volume then bounding ellipsoid, but it is harder to compute.
- **Displacement**: describes the distance of the joint or effector k towards the root of the limb, center of mass or the ground. Examples are hand-shoulder, head-root.

$$||x^k(t_i) \times x^l(t_i)|| \tag{4.10}$$

- **Rotation**: describes angular displacement v that shifts the orientation $q_k$of one joint to orientation $q_l$of another joint

$$exp(v^{kl}(t_i)) = q^k(t_i) \cdot q^l(t_i)^{-1} \tag{4.11}$$

- **Center of Mass (COM)**: describes the weighted average of the positions of joints in different body parts

$$com(t_i) = \frac{\sum_{k \epsilon K} w_k x^k(t_i)}{\sum_{k \epsilon K} w_k} \tag{4.12}$$

Effort Descriptors

Effort Descriptors are used to describe the quality of motion related to energy, dynamics and expressiveness. It is consisted from four categories: weight, time, space and flow.

- **Weight Effort**: (Hachimura K. 2005) describes it as a weighted sum of the body's, or body part's, kinetic energy calculated from the joints. Weighted effort is then calculated by estimating the maximum energy of the time interval

$$E(t_i) = \sum_{k \epsilon K} E_k(t_i) = \sum_{k \epsilon K} \alpha_k w_k(t_i) \tag{4.13}$$

- **Time Effort**: describes the sense of urgency This descriptor can by calculated by taking the sum of the accelerations, or the norm of accelerations, of the body or the different body parts over a time period (Hachimura K. 2005)

$$Time^k(t_i) = \frac{1}{T} \sum_{i=1}^{T} a^k(t_i)) \tag{4.14}$$

And for the segment of p joints

$$Time^k(T) = \sum_{k \epsilon K} \alpha_k Time^k(T) \tag{4.15}$$

- **Space Effort**: describes the directness of movement

$$Space^k(T) = \frac{||x^k(t_i) - x^k(t_{i-1})||}{||x^k(T) - x^k(t_1)||} \tag{4.16}$$

And for the segment of p joints

$$Space^k(T) = \sum_{k \epsilon K} \alpha_k Space^k(T) \tag{4.17}$$

- **Flow Effort**: describes the continuity of movement as the aggregated jerk of the body, or body parts during a time period

$$Flow^k(t_i) = \frac{1}{T} \sum_{i=1}^{T} j^k(t_i)) \tag{4.18}$$

And for the segment of p joints

$$Flow^k(T) = \sum_{k \epsilon K} \alpha_k Flow^k(T) \tag{4.19}$$

4.2.3 High-Level Motion Descriptors

In Laban Movement analysis high-level motion descriptors, as seen in Table 4.1, are divided into descriptors relating to the body, the body shape and the space where the body moves. High-level descriptors use low-level features when calculating spatial, kinematic and physical quantities that characterise the movement. This descriptors can be made at various levels of spatial discretization, on the whole body, set of joints or on one joint k.

Body Descriptors

Body descriptors describe the spatial characteristics of the motion and determine the movement of body parts. This component contains the balance, support and the center of mass displacement.

- **Action Presence**: describes if the displacement of the body segment crosses a set threshold

$$Action^k(t_i) = ||x^k(t_i) - x^k(t_{i-1})|| > \epsilon(?1 : 0) \tag{4.20}$$

- **Center of Mass Displacement**: describes displacement of the center of mass in relation to it's starting point

$$com - disp(t_i) = ||com^k(t_i) - com^k(t_{rest})|| \tag{4.21}$$

- **Balance**: describes the Boolean value of the center of mass in relation to the projection of the bounding shape on the floor. If the center of mass is out of the shape, it is considered out of balance
- **Support**: defines the current body segment that is used for support of the body

Space Descriptors

These descriptors relate the movement of the body to the 3D environment which surrounds it. This includes pathways and spatial patterns of the movement.

- **Distance Covered**: describes the projected distance of the Root joint on the floor during a certain time period
- **Area Covered**: describes the projected area of the Root joint on the floor during a certain time period
- **Hip Height**: describes the distance between the ground an the Root joint

Shape Descriptors

The shape descriptors are used to describe the changes in the shape of the body during movement. It can be calculated by the bounding shape surrounding the body, or the distances of the end effectors of the body. Shape descriptors consist of shape directional, shape flow and shaping.

- **Bounding Volume**(Shape Flow) describes the volume of the body or body parts, which is computed from the bounding shapes mentioned in the low-level descriptors on Figure 4.1.
- **Shape Directional** describes the path on which the movement is executed. This descriptor associates kinematic and geometric properties of motion. One way of calculating it is defined by calculating the average curvature in 2D, which is obtained trough PCA analysis.

$$ShapeD^k(T) = \sum_{i=1}^{T} C^k(t_i) \tag{4.22}$$

- **Extensiveness**: describes the maximum distance between the body's center of mass and the extremities, like hands, feet, head etc.

$$Extens_m(t_i) = max\, \alpha^k ||com(t_i) - x^k(t_i)|| \tag{4.23}$$

- **Arms Shape**: describes the the distance between the arm system and the body center

- **Elbow Flexion**: describes the elbow flextion angles
- **Shoulder Angle**: describes the angle between the axis defined by the arm and the vertical axis of the torso
- **Hands Relationship**: describes the distance in 3D of the hands
- **Feet Relationship**: describes the distance in 3D of the feet

4.3 Principal Component Analysis

In this report, Principal Component Analysis was used only as a dimensionality tool. As mentioned in (Reddy et al. 2020), PCA is a statistical procedure that uses orthogonal transformation. As an input, it takes in variables that are correlated and gives variables that are uncorrelated. It is usually used to compare the relationship between a group of variables, so it can be used for reducing the dimensions.

Procedure for reduction if assumed that dataset $x^{(1)}, x^{(2)}, x^{(3)}, ...x^{(m)}$ with n dimensions is reduced to k dimensions:

1. **Standardization**: data should have unit variance and zero mean

$$x_j^i = \frac{x_j^i - \overline{x_j}}{\sigma_j} \tag{4.24}$$

2. **Calculating Co-variance Matrix**

$$\sum = \frac{1}{m} \sum_i^m (x_i)(x_i)^T \tag{4.25}$$

3. **Calculating Eigenvector and Eigenvalue of the Co-variance matrix**

$$u^T \sum = \lambda \mu \tag{4.26}$$

$$U = [u_1 u_2 ... u_n] \tag{4.27}$$

4. **New Data with k Dimensions**

$$x_i^{new} = \begin{bmatrix} u_1^T x^i \\ u_2^T x^i \\ . \\ . \\ . \\ u_k^T x^i \end{bmatrix} \tag{4.28}$$

5 Results

In this chapter, the workflow of the project will be presented, together with the data analysis and results. Because of the fact that this paper is trying to classify general movement, human expression and intent, it was important to separate the data in a way that it can be distinguished from one another. This will help in the classification later. Figure 5.2 shows the workflow of the data analysis.

After the experiment and the data collection, explained in the Chapter 3, a large quantity of unsorted data was gathered. XSense MVN Awinda software was used to convert the data in 40 excel files, which contained relevant and not relevant data. Every participant's data was divided in to the transport and draping task. Data sheet of each participant/experiment contains movement data, as seen from Table 5.1.

<table>
<tr><th>Sheet</th><th>Types</th><th>Data Points</th></tr>
<tr><td>Segment Orientation</td><td>Quaternion (q1,q2,q3,q4)
Euler (x,y,z)</td><td rowspan="6">head
neck
four vertebra (L5, L3, T8, T12)
left and right shoulders
upper arms
forearms
hands
upper legs
lower legs
feet
toes
pelvis</td></tr>
<tr><td>Segment Position</td><td>(x,y,z)</td></tr>
<tr><td>Segment Velocity</td><td>(x,y,z)</td></tr>
<tr><td>Segment Acceleration</td><td>(x,y,z)</td></tr>
<tr><td>Segment Angular Velocity</td><td>(x,y,z)</td></tr>
<tr><td>Segment Angular Acceleration</td><td>(x,y,z)</td></tr>
<tr><td>Joint Angles</td><td>(x,y,z)</td><td rowspan="2">joints of the body</td></tr>
<tr><td>Joint Ergonomic Angles</td><td>(x,y,z)</td></tr>
<tr><td>Center of Mass</td><td>(x,y,z)</td><td>CoM position
CoM velocity
CoM acceleration</td></tr>
</table>

Table 5.1: *Excel sheet of the collected movement data*

The first division of data was made in terms of the task. Data was separated on data related to transport task, and data related to draping task. Visualisation of the data separation can be seen in Figure 5.1.

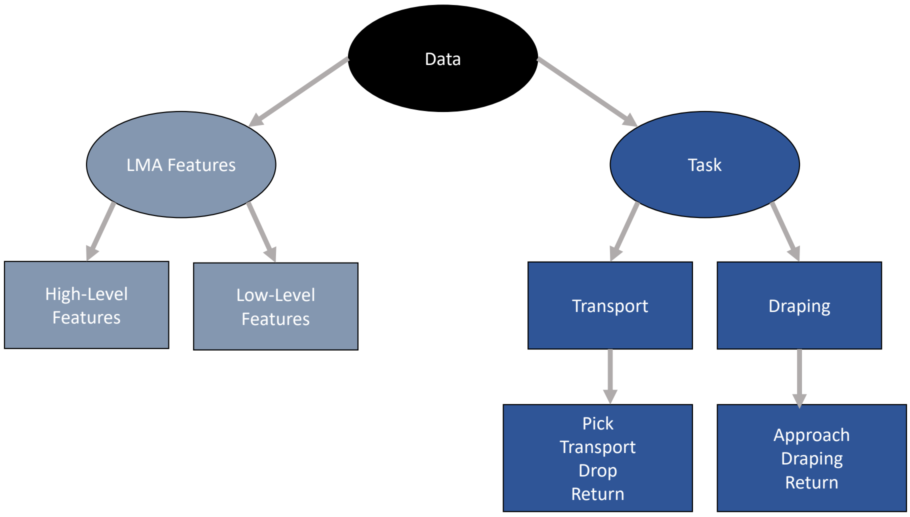

Figure 5.1: *Data separation*

As can be seen, the data was separated in two steps. One step was to calculate the Laban Movement Analysis features by following the method from Section 4.2. As explained in the earlier chapter, this divides the features into high-level and low-level descriptors. The other division step was to separate the data by the task and by the specific movement that is happening inside of the task.

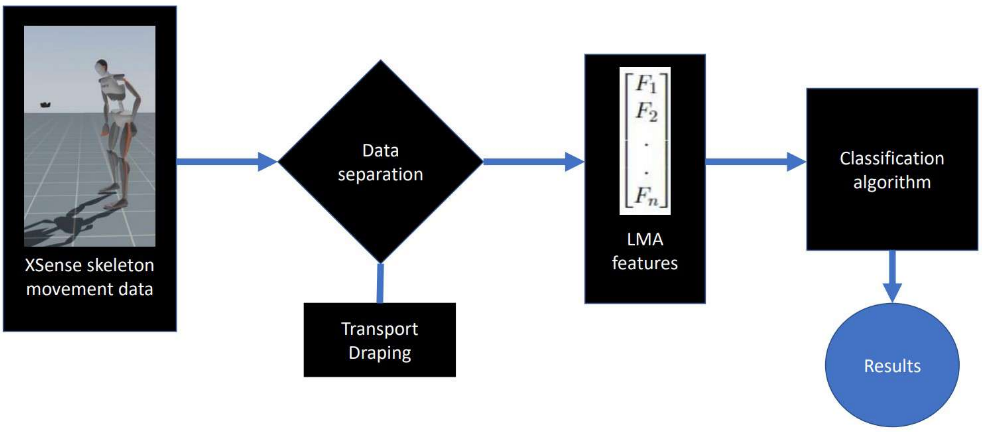

Figure 5.2: *Data analysis workflow*

5.1 Data Separation by Task

As mentioned, and seen in Figure 5.1, the data separation based on task is divided to the transport and draping. After looking for a way to separate the data in a standardised way related to the movement inside of the task, the conclusion was to look at the movement data as a signal. One of the XSense MVN Awinda sensors was placed on the end effector of the robotic arm that was doing the collaborative task with the participants. This sensor captured the information in a same way as the body sensors. Figure 5.3 shows this sensor.

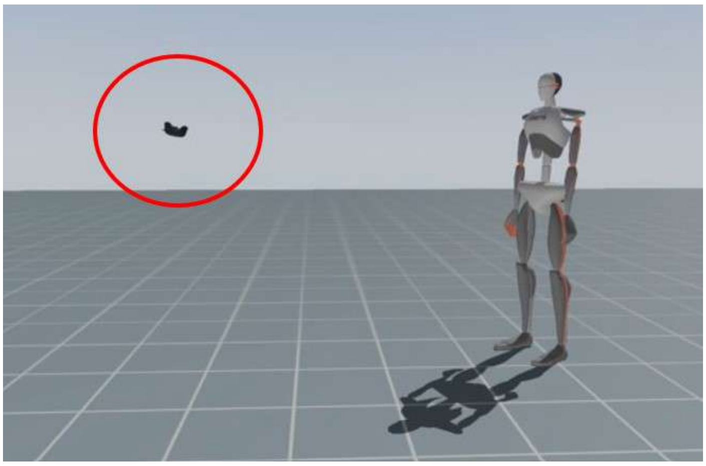

Figure 5.3: *Sensor of the robotic arm*

Movement of this sensor in the X-axis was used as the indicator of the task. As shown in Figure 5.4, peaks and minimums of the robot movement in X-axis was found with the help of the second derivation of the movement. After the needed minimums and peaks were found, the whole movement was divided. Figure 5.4 shows the division of draping on draping, approach and return. Transport was divided in to pick, transport, drop and return by the same principle.

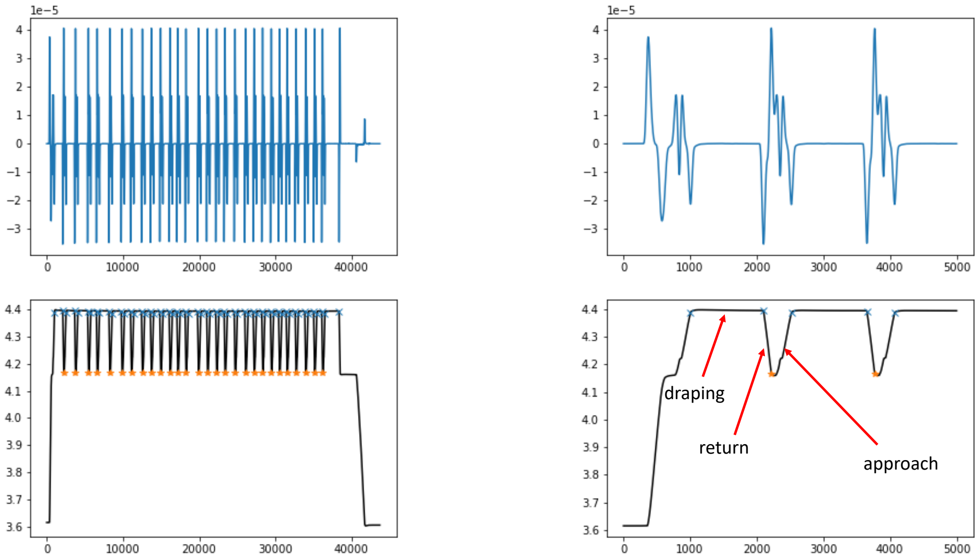

Figure 5.4: *Robot movement separation in X-axis*

6 Discussion

7 Further Work

Bibliography

Abdelhakim Cherouat Houman Borouchaki, J.-L. B. (2005). "Geometrical and mechanical draping of composite fabric". In: *Revue Européenne des Éléments Finis*.

Barbic J., S. A. (2004). "Segmenting motion capture data into distinct behaviors." In: *Proceedings of Graphics Interface*.

Caroline Larboulette, S. G. (2016). "A Review of Computable Expressive Descriptors of Human Motion". In:

Catherine Pelachaud Jean-Claude Martin, E. A. (2007). *Intelligent Virtual Agents*. Springer.

Chang S.Nam, J. B. L. (2021). *Trust in Human-Robot Interaction*. Academic Press.

Chiuhsiang Joe Lin, R. P. L. (2022). "Classification of mental workload in Human-robot collaboration using machine learning based on physiological feedback". In: *Journal of Manufacturing Systems*.

Fod A. Mataric M.J., J. O. (2002). "Automated derivation of primitives for movement classification." In: *Autonomous Robots*.

Hachimura K. Takashina K., Y. M. (2005). "Analysis and evaluation of dancing movement based on lma." In: *IEEE Intl. Workshop on Robot and Human Interactive Communication*.

HORIZON2020 (Dec. 2022). *Human-robot collaboration on draping of composite parts*. https://cordis.europa.eu/project/id/101006732. Accessed on 2022-11-12.

JavaTpoint (Dec. 2022). *Supervised Machine Learning*. https://www.javatpoint.com/supervised-machine-learning#:~:text=Supervised%20learning%20is%20the%20types,tagged%20with%20the%20correct%20output.. Accessed on 2022-11-12.

Kadir Alpaslan Demira Gözde Dövena, B. S. (2017). "Industry 5.0 and Human-Robot Coworking". In: *Mugla Journal of Science and Technology*.

Kahol K. Tripathi P., P. S. (2004). "Automated gesture segmentation from dance sequences." In: *Automatic Face and Gesture Recognition*.

Lee N. T. Resnick P., B. G. (2019). "Algorithmic bias detection and mitigation: Best practicesand policies to reduce consumer harms." In: *Brookings Institute: Washington, DC, USA*.

Lee, E. (2021). "How do we build trust in machine learning models?" In: *SSRN Electronic Journal*.

Peter A. Hancock, D. R. B. (2011). "A Meta-Analysis of Factors Affecting Trust in Human-Robot Interaction". In: *Human Factors: The Journal of the Human Factors and Ergonomics Society*.

Reddy, G. T. et al. (2020). "Analysis of Dimensionality Reduction Techniques on Big Data". In: *IEEE Access*.

Schaefer, K. E. (2016). "Measuring Trust in Human Robot Interactions: Development of the "Trust Perception Scale-HRI"". In: *Robust Intelligence and Trust in Autonomous Systems*.

Sheridan, T. B. (2016). "Human–Robot Interaction: Status and Challenges". In: *SAGE Journals*.

T.Arai R.Kato, M. (2010). "Assessment of operator stress induced by robot collaboration in assembly". In: *CIRP Annals*.

Theresa Law, M. S. (2020). "Trust: Recent Concepts and Evaluations in Human-Robot Interaction". In:

Vectornav (Dec. 2022). *What is an internal measurement unit?* https://www.vectornav.com/resources/inertial-navigation-articles/what-is-an-inertial-measurement-unit-imu. Accessed on 2022-14-12.

Wikipedia (Nov. 2022a). *HRI*. https://en.wikipedia.org/wiki/Human%E2%80%93robot_interaction. Accessed on 2022-29-11.

– (Nov. 2022b). *Isaac Asimov*. https://en.wikipedia.org/wiki/Isaac_Asimov. Accessed on 2022-25-11.

Yoshikawa, T. (2020). "Machine learning for human movement understanding". In: *Advanced robotics*.

Zhao L., B. N. (2005). "Acquiring and validating motion qualities from live limb gestures." In: *Journal of Graphical Models*.

A Trust Questioner

Interpretation of the 40 item scale. The 40 item human-robot trust scale provided an overall percentage score across all items. Items were preceded by the question "What percentage of the time will this robot …" followed by a list of the items. Each item was a single word or short phrase, and the order of items was randomized for each participant. The finalized 40 item scale is provided in Table 35, and took between 5-10 minutes to complete.

Table 35

Finalized Trust Scale

What % of the time will this robot…	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Act consistently*	o	o	o	o	o	o	o	o	o	o	o
Protect people	o	o	o	o	o	o	o	o	o	o	o
Act as part of the team	o	o	o	o	o	o	o	o	o	o	o
Function successfully*	o	o	o	o	o	o	o	o	o	o	o
Malfunction ^{R}*	o	o	o	o	o	o	o	o	o	o	o
Clearly communicate	o	o	o	o	o	o	o	o	o	o	o
Require frequent maintenance ^{R}	o	o	o	o	o	o	o	o	o	o	o
Openly communicate	o	o	o	o	o	o	o	o	o	o	o
Have errors ^{R} *	o	o	o	o	o	o	o	o	o	o	o
Perform a task better than a novice human user	o	o	o	o	o	o	o	o	o	o	o
Know the difference between friend and foe	o	o	o	o	o	o	o	o	o	o	o
Provide Feedback*	o	o	o	o	o	o	o	o	o	o	o
Possess adequate decision-making capability	o	o	o	o	o	o	o	o	o	o	o
Warn people of potential risks in the environment	o	o	o	o	o	o	o	o	o	o	o
Meet the needs of the mission*	o	o	o	o	o	o	o	o	o	o	o
Provide appropriate information*	o	o	o	o	o	o	o	o	o	o	o
Communicate with people*	o	o	o	o	o	o	o	o	o	o	o
Work best with a team	o	o	o	o	o	o	o	o	o	o	o

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Figure A.1: *Trust questioner (Schaefer 2016)*

What % of the time will this robot…	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Keep classified information secure	o	o	o	o	o	o	o	o	o	o	o
Perform exactly as instructed*	o	o	o	o	o	o	o	o	o	o	o
Make sensible decisions	o	o	o	o	o	o	o	o	o	o	o
Work in close proximity with people	o	o	o	o	o	o	o	o	o	o	o
Tell the truth	o	o	o	o	o	o	o	o	o	o	o
Perform many functions at one time	o	o	o	o	o	o	o	o	o	o	o
Follow directions*	o	o	o	o	o	o	o	o	o	o	o

What % of the time will this robot be …	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Considered part of the team	o	o	o	o	o	o	o	o	o	o	o
Responsible	o	o	o	o	o	o	o	o	o	o	o
Supportive	o	o	o	o	o	o	o	o	o	o	o
Incompetent ^{R}	o	o	o	o	o	o	o	o	o	o	o
Dependable *	o	o	o	o	o	o	o	o	o	o	o
Friendly	o	o	o	o	o	o	o	o	o	o	o
Reliable *	o	o	o	o	o	o	o	o	o	o	o
Pleasant	o	o	o	o	o	o	o	o	o	o	o
Unresponsive ^{R} *	o	o	o	o	o	o	o	o	o	o	o
Autonomous	o	o	o	o	o	o	o	o	o	o	o
Predictable *	o	o	o	o	o	o	o	o	o	o	o
Conscious	o	o	o	o	o	o	o	o	o	o	o
Lifelike	o	o	o	o	o	o	o	o	o	o	o
A good teammate	o	o	o	o	o	o	o	o	o	o	o
Led astray by unexpected changes in the environment	o	o	o	o	o	o	o	o	o	o	o

Note. The 14 trust subscale items are marked with an *.
The R represents reverse coded items for scoring.

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Figure A.2: *Trust questioner (Schaefer 2016)*