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Capturing Body Language in Engineering Design – Tools and Technologies

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Abstract

This paper presents an attempt to make three contributions to engineering design literature on the topic of body language. Firstly, through a brief overview of existing work on the role of body language in engineering design, we propose the need for alternative tools and technologies to manual video coding. Manual video coding is time and resource consuming, and we believe that certain parts of data collection and analysis could be automated. Secondly, common tools for body language analysis not limited to engineering design is presented. These are manual video coding, vision-based motion capture, reflector-based motion capture, and inertial sensor-based motion capture. Each is presented together with a discussion of strengths and limitations, and potentially relevant use cases. Lastly, a pilot study regarding the application of a few, simple inertia-based sensors to recognise gesturing activity is shown. Wrist-mounted accelerometers were used to measure gesturing activity. This activity was compared to video material of the test subjects. Results from the pilot indicates that acceleration above a certain threshold could be linked to gesturing activity.

Keywords: body language, engineering design, sensors, quantitative data, motion capture

1 Introduction and Background

In this paper, we attempt to make three contributions to current literature on body language in engineering design. Firstly, we present a brief overview of previous work done in this field. Most of the work focuses on the role of gestures as a communication channel for forming and sharing ideas. These studies rely on the use of manual video coding as analysis method, which is time and resource consuming. Secondly, we provide an overview of tools and technology that are commonly used within research on body language as a general topic. Pros and cons of each of these tools and technologies are discussed, and recommendations for use in the field of engineering design research are provided. Lastly, based on recommendations from the second contribution, a pilot study is presented, aiming to investigate if it is possible to use a few, simple inertia-based sensors for recognising gesturing activity. This study was done by using wrist-mounted accelerometers. Based on comparison between video and sensor output data, there is an indication that hand gesturing activity can be recognised when acceleration exceeds 0.4 m/s^2.

Body language is extremely complex. There is not one single 'channel' of data, but rather a vast number of different information channels, e.g. facial expressions (Hwang & Matsumoto, 2016), gestures (Cartmill & Goldin-Meadow, 2016), and body movement (Matsumoto, Hwang & Frank, 2016). The probably two most relevant aspects of body language for engineering design research are the ability to enact physical concepts and ideas (Cash & Maier, 2016), and to communicate emotion (Jung, 2011). The role of hand gestures in engineering design activities has been studied by several researchers. Tang & Leifer (1991) uncover how gestures play an important role in demonstrating actions and establishing common understanding during sketching exercises. This is corroborated by Eris, Martelaro, & Badke-Schaub (2014) that show how gesturing is related to sketching. Cash & Maier (2016) investigate how archetypical gesture sequences occur at critical stages in the design process. They emphasise that in addition to play an important role in forming ideas and concepts, gestures also strongly contribute to develop shared understanding through mirroring and adaption of gestures. Edelman (2011) show some qualitative data that design teams using gestures to enact their ideas come up with more novel results. Jung (2011) explore how the emotional state of team members, elicited from facial expressions, influence team performance.

Until now, the most common way of approaching body language in engineering design contexts has been to apply the tool of manual video coding (section 3.1). This is time and resource consuming for the researchers, and due to the amount of time and effort required, it is difficult to process enough data to apply robust statistical analyses.

Progress made in motion capture technology and the field of artificial intelligence opens up possibilities when studying body language. Eventually these technologies will enable at least parts of data gathering and processing to be done automatically. Data can be captured by camera- and sensor-based solutions, and later processed by classifying behaviour based on predefined movement patterns or automatically clustering data to identify new behaviour patterns.

2 Tools and Technologies for Body Language Analysis

In order to quantify the effect of body language, we need tools for capturing data. This section presents some of the more commonly used tools and technologies when studying body language.

We separate measuring body language into manual and automatic tools (Figure 1). The manual tools include direct human observation and manual video coding. Automatic tools make use of sensors and intelligent data processing for clustering and classification, without humans having to interpret all the data. The tools can further be placed in two broad groups, camera-based and wearable-based. Camera-based tools rely on external cameras, recording the subject, to gather data. Wearable-based tools require subjects to wear sensors on their body for data collection.

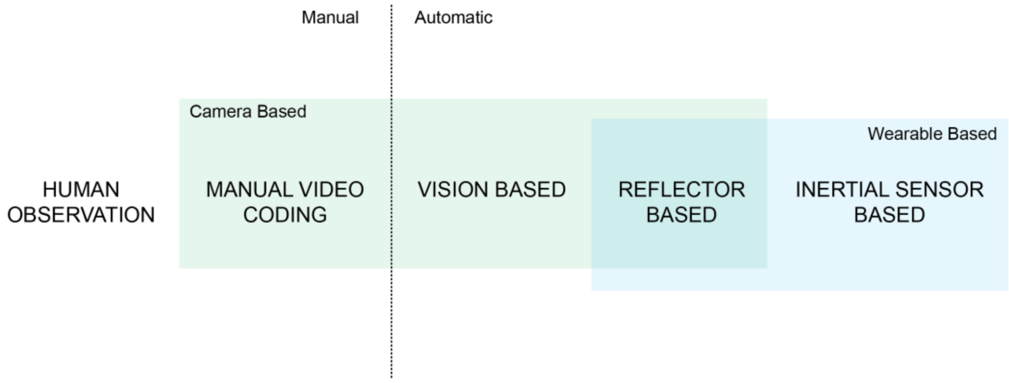

Figure 1. Grouping of technologies

Prior to applying any sort of quantitative analysis to selected situations or contexts, it is useful to apply the “tool” of human or direct observation (Dael, Bianchi-Berthouze, Kleinsmith, & Mohr, 2016). Human observation is based on the observer making judgements of what they see in real time, as opposed to recording data in one way or another for later more detailed analysis. This tool is highly qualitative, and is meant to provide an overview of the situation or context of interest, preparing the researcher for later stages of their research projects. By spending some time observing subject behaviour and movement, the researcher should be able better able to shape the later quantitative analysis in terms of detail and focus (Dael et al., 2016).

2.1 Manual Video Coding

The most common method for body language analysis is through manual video coding. Coders review video recorded during experiments and annotate with context relevant codes. These can either be pre determined to support (or reject) existing hypotheses, or emerge during the coding process if using a grounded approach (Glaser & Strauss, 2009). There are two main approaches when deciding how to treat video content: functional coding and anatomical coding (Dael et al., 2016). Functional coding focus on the function of what is done, e.g. reaching, pointing, picking up. Anatomical coding describes the movement made and orientation from an anatomical standpoint, e.g. right head tilt. There are two common techniques for sampling data in manual video coding; event coding and interval coding (Dael et al., 2016). When applying event coding to material, the coder classifies codable events whenever they occur. Conversely, for interval coding, time is divided into a number of intervals and classified by each intervals content.
Dael et al. (2016) describe a typical coding process where two or more coders first go through part of the material individually and then run through an intercoder agreement test. After this test, coders discuss areas of disagreement and adjust or remove codes accordingly. Finally, the entire corpus of the material can be coded with this new set of agreed upon codes.

Studies of the role of body language in engineering design heavily rely on manual video coding. Most of them are focused on which role gesture plays in design activities (Cash & Maier, 2016; Edelman, 2011; Eris et al., 2014; Tang & Leifer, 1991). Jung (2011) explored how the emotional state of engineering design team affected the outcome through several tools, facial coding as a proxy for team members emotions being one of them.

Manual video coding is time and resource consuming. A rule of thumb is that five minutes of raw video take up to one hour to code. This limits the amount of data that can be coded within reason for one study, and it is thus difficult to have large enough test samples in studies to apply robust statistical methods. In addition to the video coding itself being time consuming, coders must be trained on how to code in order to get coherent results (Dael et al., 2016). The real advantage of manual video coding is the flexibility of a human coder, able to pick up subtle nuances that is difficult to predict a priori. This is especially important when developing a coding scheme for the first time, discovering potential interesting patterns to later be investigated with a structured coding scheme. Being entirely camera-based, manual video coding can be considered unintrusive due to the fact that subjects are not required to attach any form of sensors on their bodies as opposed to the wearable solutions for body language acquisition.

We suggest that manual video coding should be considered in body language studies, where human coders are needed to infer meaning from highly context dependent, ambiguous behaviour. This tool is excellent for fine grained analysis of human behaviour, taking advantage of human ability to understand complex behaviours. Due to the time and resources needed for manual video coding, it is mostly suited for studies with limited data, such as exploratory studies aiming to define suitable research questions. For studies with larger amounts of data, we would recommend considering one of the tools described in the coming sections.

2.2 Vision-Based Motion Capture

Recent development of cheaper sensors and increased computing power has led to motion capture solutions like the Microsoft Kinect™ and other webcam-based systems. These solutions are not dependent on the user wearing a certain type of sensor on their body, but rather try to extract information of body movement from image recognition techniques. The Kinect use an infrared camera the project an infrared pattern that enables depth recovery of motion (Dael et al., 2016). From this information, either a skeleton structure of the subject can be reconstructed (Sudderth, 2006) or a geometric descriptor without any clear anatomical meaning can be used for movement interpretation (Kurakin, Zhang, & Liu, 2012). Similar to using the Kinect, regular cameras can be applied to tracking as well, but without depth data. These systems rely purely on contrasts and colour in the picture to extract information.

Over the last few years, we have seen several studies where depth sensors are applied to the study of body language. Zhang (2012) provide an overview of where depth cameras can be applied. Kurakin et al. (2012) describes how depth cameras can be used to recognize dynamic hand gestures in real time by using geometric descriptors. The study made by Gabel, Gilad-Bachrach, Renshaw, & Schuster (2012) showcase a method for full body gait analysis with a virtual skeleton structure as input using the Kinect, and Stone & Skubic (2011) made a comparison of how web cameras and the Kinect could be used to measure gait.

Vision-based motion capture is a low cost motion tracking technology where most of the value is added in software post-processing. The most important advantage of vision-based motion capture is in our opinion the possibility of capturing movement without the need to wire up subjects. Due to the low cost of depth sensors, e.g. a Microsoft Kinect costs $99, we see an emerging community developing open source software that can be used for free by researchers. There are some limitations to vision-based motion capture. One of the most apparent issues is that of occlusion (Mitra & Acharya, 2007). Occlusion is an issue for all camera-based technologies, where parts of the subject is hidden from view. This bring us to an associated limitation; skeletal tracking structures has to be manually reconstructed after tracking errors, costing a lot of time and effort. In addition to tracking errors due to occlusion, we have also found there to be some issues related to tracking in various light conditions. This was especially true for infrared radiation from sunlight. In an engineering design setting, there is usually several people involved, moving around to use whiteboards and prototyping materials as some of the possible activities. The Microsoft Kinect™ has a limited tracking envelope, which is very vulnerable to occlusion from subjects. It is possible to connect multiple depth sensors/cameras together for better results (Berger et al., 2011). This requires calibration and precise setup of cameras to work. Using purely vision-based tools for motion tracking will limit how accurately body parts can be tracked due to limitations of resolution and camera placement. This is especially true for hand and finger movement because of occlusion between fingers and subtle movements. If hand and finger movement is the interest of the study, camera sensors need to be positioned close by, thus limiting the ability to track the rest of the body.

Vision-based motion capture systems seem most suited for settings where subjects are more or less stationary, and the chance of occlusions is relatively low. This technology is suitable for studies either where relevant movement and behaviour can be identified by intelligent algorithms, or studies where the researcher is searching for recurring patterns of movement or behaviour. Vision-based systems' accuracy is limited by subject distance to the camera sensor and the possibility of occlusions. This should be kept in mind when designing experiments, deciding what level of detail is needed.

2.3 Reflector-Based Motion Capture

Reflector-based motion capture is a technology widely used in both film and gaming industries for animation, and has later been adopted into biomechanical analysis such as 'full body movement' and 'gait analysis'. This technology make use of (generally 8-12) infrared cameras tracking retro-reflective markers placed on the body (Dael et al., 2016). This data can then be represented in various detail levels, such as skeletal structures or point-light displays (Ma, Paterson, & Pollick, 2006).

The survey by Kleinsmith & Bianchi-Berthouze (2013) discusses automatic recognition of emotions using body language as at least one input modality. They describe point-light displays from IR-reflector systems as one way to collect data. Pollick, Paterson, Bruderlin & Sanford (2001) use reflector-based motion capture to show that it is possible to discern subjects emotional state from point-light displays of arm movement. Roether, Omlor, Christensen & Giese (2009) use the same approach to investigate the perception of emotion from gait.

Reflector-based motion capture systems are highly accurate due to triangulation of reflector positions from the multi-camera setup normally used, combined with known position of the retro-reflective markers placed on the subject's body. Using this technology, a precise numerical representation of the subject's body can be represented in three-dimensional space, either as Cartesian coordinates or as Euler rotation angles (Dael et al., 2016). Compared to the vision-based solutions, reflector-based motion tracking is quite expensive. This can be justified when comparing the tracking accuracy, and the trade-off between price and accuracy should be considered for each tracking experiment. As with vision-based motion tracking, reflector-based tracking require manual cleaning of data due to occlusion. The need for manual cleaning of data means that reflector-based motion tracking is less suitable for real-time applications. One more disadvantage of the reflector-based systems is mobility. Requiring 8-12 cameras to be set up and calibrated to track with high accuracy is time and labour intensive. In addition to this, there are issues with varying light conditions, skin tone, clothing and touching that may cause errors in automatic extraction of body parts with this technology. Reflector-based motion capture systems usually have the capability to track more than one person at a time. This is highly beneficial in an engineering design context, where there usually are two or more persons working together at any time. One other drawback of reflector-based motion capture is that subjects are required to wear reflectors on their body, which might make them more self conscious of their actions.

We imagine that appropriate use cases for reflector-based motion capture are quite similar to those of vision-based systems. The main difference between the two technologies is that the reflector-based systems have a higher accuracy and are more robust in terms of data capture. This is mostly due to the use of multiple cameras, but also because the markers attached to the subjects provide tracking points of known location on the body. This higher accuracy is reflected in the price of such systems, and it is therefore important to know which detail level is needed for the study. For fine detail levels, reflector-based motion capture is preferable over vision-based systems. These systems may also be very well suited for studies where multiple subjects' motions are tracked. As a side-note, it is important to keep in mind that subject behaviour can be influenced by having to wear sensors on their body, the Hawthorne effect.

2.4 Inertial Sensor-Based Motion Capture

All of the beforementioned solutions for capturing body language data have been based on external sensors in the form of cameras. As sensors get smaller and more compact, an alternative is to use active sensors attached to the subject's body. Inertial measurement units (IMUs), consisting of accelerometers, gyroscopes and sometimes magnetometers, can be placed on various body parts to give information about acceleration and orientation. This information can then be combined with biomechanical constraints and translate into position and velocity data of different body parts.

One such system is the XSens (Roetenberg, Luinge, & Slycke, 2009) that has been used in major Hollywood productions, gaming industry and biomechanical studies. Zhou, Stone, Hu, & Harris (2008) use two IMUs attached near the wrist and the elbow joint respectively to track the position and angular rotation of the wrist, elbow, and shoulder joint with the aim of monitoring the rehabilitation of patients. Zhu & Zhou (2004) also show in their research how to combine sensor input from accelerometers, gyroscopes and magnetometers in a novel way to increase tracking accuracy for arm movement.

The core strength of the inertial-based systems is that without any external sensors, the issue of occlusion is eliminated. Also, since all sensors needed for motion tracking is worn on the participant's body, the system is very mobile and can be used in almost any setting (Dael et al., 2016). This also make the tracking envelope close to infinite, as opposed to camera-based solutions that require the subject to be inside the cameras' field of view. The core issue that must be addressed when using inertia-based solutions is sensor drift (Roetenberg et al., 2009). One way to address this is by applying biomechanical constraints, i.e. knees and elbows have only one axis of rotation and limited travel range. Together with biomechanical constraints, sensor fusion algorithms (Zhu & Zhou, 2004) have made inertial-based motion tracking very accurate. The sensor fusion algorithms combine data from accelerometers, gyros and

magnetometers in a way that each sensor's weakness is countered by the other sensors' strengths. An example is that accelerometers can be used to identify the vertical axis through gravity, while magnetometers detect horizontal direction using the earth's magnetic field (Roetenberg et al., 2009). One big drawback with using inertial-based motion tracking is that magnetic sensors are incredibly sensitive to surrounding magnetic fields. This means that electrical wires and computers can influence the tracking accuracy quite considerably (Zhu & Zhou, 2004). Due to this, it is recommended to move as far away from magnetic sources as possible when tracking motion data with this technology, although magnetic disturbances can to some extent be reduced through calibration.
Inertial sensor-based systems are suitable for experiment setups where subjects are moving around. Another advantage is that the need for placing cameras with a clear field of view is eliminated, which is highly relevant for in-situ studies where spaces can be sectioned off, have big furniture, and low ceilings. This technology may be extra advantageous when tracking multiple subjects at once, since each subject's sensor data is self contained – as opposed to camera-based systems where all data is collected through cameras and has to be sorted in the software.

2.5 Back End Software Interpretation

In order to make sense of data gathered with automatic tools, we are depending on intelligent algorithms for processing and interpretation. This could be to recognise patterns that make up a gesture sequence, or a specific shape that translates into a certain posture, providing information about the subject's emotional state. Before this sort of recognition can take place, we need to transform the raw data gathered into a form that is interpretable by the recognition algorithms. This could be in the form of background extraction for vision-based tools, or using biomechanical constraints together with physical equations to translate inertial sensor-based data into the physical position of body parts.

3 Recommendations

Technology	Pros	Cons	Use cases
Manual video coding	High level of detail Flexibility of human coder Unintrusive	Time and resource consuming Intercoder reliability Limited data points	Exploratory studies Study of highly context dependent, ambiguous behaviour
Vision-based motion capture	Low cost Unintrusive Large open source community	Occlusion Manual reconstruction of data Fixed setup due to cameras and calibration Small tracking envelope	First trial of motion capture Fixed subject position Pre-defined patterns Clustering new patterns
Reflector-based	High precision Suitable for multi-	Expensive	High accuracy required Less fixed positions

motion capture	person tracking	Occlusion Manual reconstruction Fixed setup due to cameras and calibration Require the subject to wear sensors	than vision-based solutions Pre-defined patterns Clustering new patterns
Inertial sensor-based motion capture	No external sensors needed High mobility No issues with occlusion Can be used in almost all settings	Expensive Vulnerable to magnetic fields Prone to issues with sensor drift Require the subject to wear sensors	Lots of movement Many obstructions Overlapping movement of subjects Pre-defined patterns Clustering new patterns

Table 1. Comparison of tools and technologies

Based on our review of the different tools and technologies that can be used for studying body language, we believe that inertial sensor-based motion capture is very well suited for studying engineering design activities. Firstly, because this technology will require the least amount of manual filtering of data. Secondly, because inertial sensor-based systems do not depend on external sensors, they act as self contained systems and are not vulnerable to interference of other subjects' data. This is opposed to vision- and reflector-based systems where multiple subjects standing close together can lead to tracking errors.

A pilot study with inertial sensors has been conducted by the authors. Instead of striving to capture all possible information, we argue that a reasonable first step is to select a few key features to investigate in-depth, and rather expand the number of features later. For this pilot, we decided to use accelerometers attached to the subject's wrists, in an attempt to measure when gesturing activity takes place. We did not attempt to investigate the effect of gesturing activity, but rather to see if it is possible to determine when gesturing activity takes place. Data was recorded at a Design Thinking (Brown, 2008) workshop with two rounds of three participants each wearing the sensors for 30 minutes while solving ideation tasks. The sensor data was plotted and synced with video recordings to see if there was any correlation between gestures seen in the video and acceleration measured with the sensors. We found that gestures correspond to accelerations above approx. 0.4 g, and we believe that gesturing activity can be identified as time periods where the acceleration of subject hands is exceeding this threshold as seen in Figure 2.

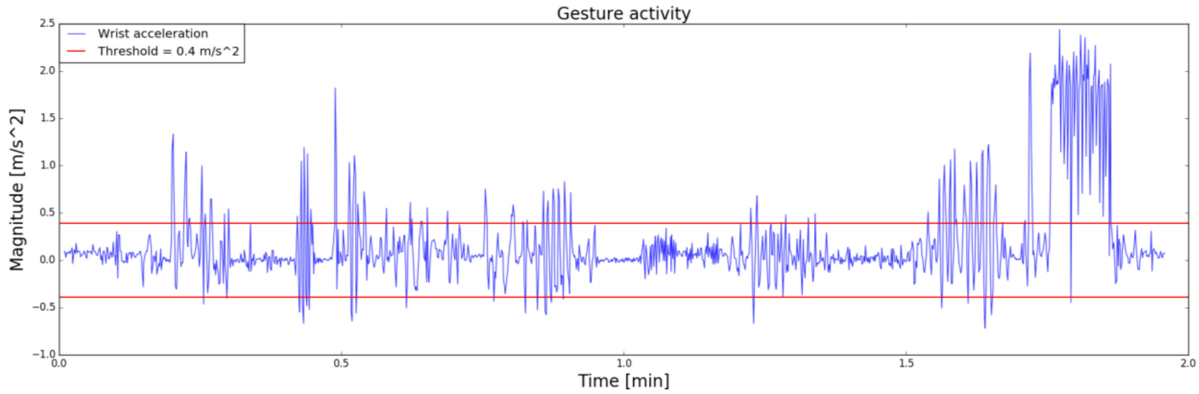

Figure 2. Wrist accelerometer data excerpt.

4 Conclusion

In this paper, attempts at three literature contributions have been made. Firstly, we provide a brief overview of existing work in the field of body language in engineering design.

Secondly, we have presented existing tools and technologies used for the study of body language. A brief explanation of how each tool is used has been provided, along with examples of how the tools have been used previously. At the end of each section, we attempt to provide the reader with recommendations of where to apply these tools for engineering design research on body language. An overview of the pros and cons of each tool, along with recommended use cases for each, is presented in a table for easier comparison (Table 1).

Lastly, we have shown how we can approach measuring body language with inertia-based sensors by using a few simple sensors attached to the wrists. Using accelerometers and comparing output with video as a reference, we have shown that acceleration exceeding 0.4 m/s^2 is an indication of gesturing activity (Figure 2).

Based on this paper, we call for further study of body language in an engineering design context using automatic data gathering tools. This should allow researchers to process much larger data sets in a shorter time, enabling the use of more robust statistical methods and saving vast amounts of time on data analysis.

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