Production and Perception of Whole- Body Movements to Probe the Social Brain

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1. Abstract

The mirror neuron system (MNS) and the mentalizing system (MENT) are considered to be key elements of social cognition. The exact roles of the two systems are yet to be clarified. In a new approach to this question, we produced a set of video stimuli to be used in an upcoming functional magnetic resonance imaging study.

We used a motion capture recording technique to map genuine human movements onto a virtual character. This yields the big advantage of being free from confounding variables such as age, gender, ethnicity or attractiveness. Furthermore the stimuli are highly controllable and can be manipulated for subsequent studies. The physical properties (e.g. luminance, movement speed) of the resulting video material were assessed with the help of an algorithm. This made it possible to exclude videos with outlier data in the mentioned physical properties. In a further step the remaining videos were rated by naïve volunteers to compute the recognition rates for each video, allowing us to filter out videos that were reliably rated correct. Thus, we generated a highly robust and homogenous set of video stimuli (validation study in preparation) to investigate the social brain (MNS, MENT).

This thesis covers the production of the stimuli, the analysis of the movement characteristics and the rating of the videos through naïve volunteers. Additional analyses of correlations between the production (subjective experience and personal characteristics of volunteers during motion capture recordings) and the subsequent perception of these recordings were carried out.

Results show no considerable correlation between personal characteristics (BIG5, empathy, emotional intelligence) and subsequent recognition rates. This can be interpreted as an indication that humans are able to recognize different moods from nonverbal behavior of others independently from the personality of the observed individual. However, we found significant correlations between the subjective immersion into a mood and the subsequent recognition rate. This means, the level of immersion into a mood has an impact on the subsequent recognizability when communicated nonverbally to other individuals.

2. Abbreviations

ASD	Autism spectrum disorder
ASTS	Aktuelle Stimmungsskala
BIG5	Big five inventory
fMRI	Functional magnetic resonance imaging
M	Mean
MENT	Mentalizing system
MNS	Mirror neuron system
ROI	Region of interest
SD	Standard deviation

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4. Introduction

Imagine you go to meet with a friend and you get to the agreed-on spot before time. Sitting there, waiting, you see your friend coming down the street. While your friend walks towards you, you have the opportunity to inspect your friend's walking movements. Normally, even a short timeframe will allow you to get an idea of your friend's mood without exchanging explicit information. For example, if the movements are fast, lively and upright, there is a good chance that your friend is in a good mood. In contrast to that, if the movements are slow, hesitant and bent, then your friend might be in a depressed mood. So, when you actually meet and start a conversation, you already have an impression about the general mood your friend might be in.

Interacting with another human being is one of the most common situations in everyday life. This seemingly trivial process is a central element of social cognition, which can be considered one of the key capacities in the evolution of the human species, as it lays the groundwork for culture, complex imitation learning and intergenerational preservation of knowledge (Tomasello, 1999).

When inferring about the inner state of the human counterpart in such interactions, verbal and nonverbal cues are interpreted. Both of these categories are believed to be of approximately equal importance in human communication (Argyle, 1990; Burgoon, Guerrero, & Manusov, 2011). Nonverbal behavior can be divided into four functional levels: (a) modeling and coordination functions, (b) discourse functions, (c) dialogue functions, and (d) socio-emotional functions (Vogeley & Bente, 2010). It is commonly agreed that nonverbal signals include facial expressions, gesture, posture and eye movements (Argyle, Salter, Nicholson, Williams, & Burgess, 1970).

The processing of nonverbal signals normally happens very fast and intuitively in typically developing individuals. Persons with *Autism Spectrum Disorder* (ASD) on the other hand, have problems with these kinds of interpretations (Kuzmanovic, Schilbach, Lehnhardt, Bente, & Vogeley, 2011; Senju, Southgate, White, & Frith, 2009). Research in nonverbal communication in ASD has provided a plethora of evidence, for example in the field of gaze (e.g. Boraston & Blakemore, 2007; Klin, Jones, Schultz, Volkmar, & Cohen, 2002; Pelphrey et al., 2002) or whole-body movements (Blake, Turner, Smoski, Pozdol, & Stone, 2003; Kaiser, Delmolino, Tanaka, & Shiffrar, 2010; for a review, see Kaiser & Pelphrey, 2012). ASD comprises a wide array of different manifestations, but especially the group of persons with ASD without learning

disabilities, often referred to as high functioning autism or Asperger syndrome (Asperger, 1944), are of high interest for research as they show impairments in social interaction and communication but not in other domains (e.g. IQ, memory, verbal abilities). Comparing behavioral and neuroimaging data of persons with and without ASD thus yields the opportunity to infer about mechanisms underlying social cognition.

In brain-imaging research within the fields of cognitive and social neuroscience, two brain networks are repeatedly presented as key regions: (a) the so-called mentalizing system (MENT) and (b) the so-called mirror neuron system (MNS). The MENT is believed to allow humans to attribute intentions, moods and other mental states to conspecifics (Frith & Frith, 2003). It is also sometimes referred to as *Theory of Mind Network* (Premack & Woodruff, 1978) or *Social Neural Network*. The MNS is attributed to action understanding and derived its name from studies in monkeys that showed neural activation both when they performed a certain action and also when they observed another monkey perform the same action (Gallese, Fadiga, Fogassi, & Rizzolatti, 1996; Rizzolatti & Craighero, 2004). The exact characteristics of the MNS in humans is a topic of controversy (e.g. Hickok, 2009), especially because a direct proof (single-cell recordings) is almost impossible to achieve. The reasons for this are the highly invasive nature of such procedures and the ethical implications thereof. On rare occasions, there is a chance to record cellular activation on such a level, e.g. when patients with pharmaceutical intractable epilepsy agree to intracranial implantation of depth electrodes to potentially locate seizure foci for possible subsequent surgical treatment. However, it should be noted that the evidence for the existence of the human MNS is accumulating. Some neuronal recordings have been reported, but only for limited areas (medial frontal and temporal cortices) by Mukamel, Ekstrom, Kaplan, Iacoboni, & Fried (2010). In a recent publication further corroboration was found in left hemispheric stroke patients (Binder et al., 2017). For a review on MNS, see Rizzolatti, Cattaneo, Fabbri-Destro, & Rozzi (2014).

The exact roles and interrelations of the MNS and MENT during social cognition are, as of yet, not cleared up and a matter of current research. Very recently a hypothesis was put forward by Vogeley (2017), who suggests that the MNS serves as a detection system to scan the observed motion for socially salient information. The MENT subsequently evaluates actually socially salient information. The hypothesis is based on the recent findings in neuroscience.

Most experimental setups to date used substantially different stimuli for the separate networks: videos of biological motion were used to activate MNS while written or spoken stories with questions about beliefs or intentions of the protagonists were used for MENT (for an overview, see Van Overwalle & Baetens, 2009). To compare both systems more precisely than previously possible it would be ideal to have stimulus material that would activate both systems separately. Showing the same visual input in both conditions would especially help to get rid of confounding brain activity when undergoing fMRI. This hypothesis led to the development of the stimuli as described below and is the goal of the overarching project that this study is embedded in.

To this end, we produced a set of video stimuli that will differentially activate both systems (validation study currently in preparation). The key feature of these stimuli will be that they show exactly the same visual information and at the same time allow to differentiate the two different networks. Only the instructions for the participants will differ. Having the same psychophysical input for both conditions will allow for a much cleaner comparison between brain activation patterns. For the maximum control of physical features we chose to use motion capture recordings rather than classic video material. With the motion capture data we were able to transfer genuine human movements onto a virtual character. By doing this we reduced confounding attributes that would be visible in normal video material: gender, ethnicity, age, attractiveness and other personal characteristics. The usage of such virtual characters has been proven to be ecologically valid (Vogeley & Bente, 2010). To activate MNS and MENT via the same visual input we came up with the design that shows everyday movements (e.g. mopping, sweeping for MNS activation) that are conducted in different moods (e.g. happy, angry for MENT activation). While the former asks the viewer to classify the action by motion detection as a classic MNS-task, the latter asks the viewer to look “behind” the movement to infer about the inner state of the protagonist, thus resulting in MENT-activation.

This thesis summarizes the production process, a computational selection procedure, stimulus rating by naïve volunteers and statistical analysis of the resulting data. Additionally to the stimulus production we investigated some interesting research questions. It was agreed that we would assess demographic and psychological data about the volunteers that would participate in the motion capture recordings. This would allow to compare production (subjective experience and personal characteristics of volunteers) and perception of everyday movements. The literature

research showed little results for a direct correlation of personal characteristics and subsequent perception. Previous studies in similar contexts either did not assess the experience of the persons during movement production (Atkinson, Dittrich, Gemmell, & Young, 2004; Montepare, Goldstein, & Clausen, 1987; Wallbott, 1998) or did not correlate this experience during production with the movement perception during observation (Michalak et al., 2009).

One would intuitively assume that persons with high empathy and/or emotional intelligence scores would be better at immersing into a specific mood and consequently portraying this mood through nonverbal behavior (body movements). As this was not previously investigated we asked the questions: Does personality affect the ability to portray a certain mood? Will empathy or emotional intelligence correlate with this ability?

Besides a connection of production and perception, we wanted to investigate the interrelations between production and movement characteristics. Michalak et al. (2009) showed significant differences between depressed and never depressed individuals with concern to movement speed. Thus, we speculated that in our experimental setup the sad movements would be slower when compared to the other two (happy, angry).

One study found a correlation between neuroticism (measured with the Big Five Inventory) and movement speed (Luck, Saarikallio, & Toiviainen, 2009). It should be noticed here, that the results of Luck et al. were not robust (small sample size, small significance) and with our data we are following up on this results to either corroborate or refute the preliminary results.

5. Materials and Methods

5.1. Motion Capture Recordings

5.1.1. Motion Capture Recordings: Participants

We recruited 31 volunteers (17 females, mean age = 25.55, $SD = 6.01$) via (a) mailing lists of the study programs Psychology and Neuroscience of the University of Cologne, (b) word of mouth or (c) publicly visible notices. All participants were informed about the procedures and the scientific background of the envisaged use of their motion recordings as stimulus material and gave informed consent prior to participation. All participants were either compensated monetary (15€) or with credits for participation. Four participants had to be excluded due to

technical issues. Five other participants were excluded because they stated that they didn't empathize sufficiently with the demanded moods during the procedure (see 5.1.2. for details).

5.1.2. Motion Capture Recordings: Procedure

Before the motion capture recordings began, participants gave informed consent and filled out a survey via computer which included various demographic information (age, gender, handedness, etc.), as well as some basic psychological traits: We used a short version of the *Big Five Inventory* (Rammstedt & John, 2007), the *Toronto Empathy Questionnaire* (Spreng, McKinnon, Mar, & Levine, 2009), the *Emotional Intelligence Scale* (Schutte et al., 1998) and repeatedly throughout the whole process of recording the *Aktuelle Stimmungsskala* (ASTS) (Dalbert, 2009). Some of this information about the participants is intended to build the metadata of a motion capture database and was not evaluated in the course of this study. Our analysis focused on the psychological traits and the correlations to the subsequent recognition rate (see 6.2.).

The recordings were conducted in cooperation with the research group *AG Medienpsychologie* of the University of Cologne, headed by Prof. Dr. Gary Bente (now: Michigan State University, USA).

Participants performed six everyday movements in three different moods (see Table 1) resulting in 18 recordings per participant. The selection of movements was tested in a pre-study, which ensured that movements were not too easy to keep apart. For instance we excluded screwing with a screwdriver and hammering with a hammer, because both of these movements were far too easily distinguished.

Table 1

Actions and Moods Recorded in the Motion Capture Setup

Actions		Moods
1. Mopping	2. Sweeping	1. Happy
3. Wiping a Table with a Rag	4. Sanding a Piece of Wood on a Table	2. Angry
5. Painting a Wall with a Brush	6. Painting a Wall with a Roller	3. Sad

X

Note. All six actions were performed in three designated recording blocks for each mood.

In order for the participants to execute the different movements naturally while displaying the different moods, we used a mood induction procedure and very specific instructions. Instructions were presented as audio recordings, the volunteers listened to before each of the 18 recordings. Mood induction was achieved by an *Imagination Mood Induction Procedure*, which is considered to be one of the most effective ways to induce different moods (for a meta-analysis of different possible procedures, see Westermann, Spies, Stahl, & Hesse, 1996).

To give an example, the instruction for *happy sweeping* asked the participants to imagine something to happen to them that would make them “really, really happy”. The instruction then asked the participants to imagine this event in as much detail as possible and to immerse into the associated mood (here: happiness) as best as possible. The instruction ended with the statement that the participants should take their time and when they felt ready they should start to sweep the area in front of them.

The order of the three moods was randomized for each participant. The recordings were thus organized in three recording blocks: happy, angry, and sad. In each of these blocks the volunteers performed the six actions in the same order (see Fig. 1). To control for immersion of the volunteers into the different moods several steps were taken: (a) Participants completed the ASTS before the first and between recordings, (b) after each recording block the participants level of immersion into the demanded mood was assessed via a Likert scale ranging from 1 (*not at all*) to 11 (*very well*). Participants data as a whole was excluded from further processing if

they responded with a value equal to or smaller than 5 for any of the recording blocks, (c) participants were asked to briefly describe the situation(s), which they imagined in order to immerse into the different moods. Directly before the next recording block they were presented with a relaxation-video (showing a tree with relaxing background music) to neutralize the mood. This was again controlled by another ASTS for the current mood (see Fig. 1 for a schematic overview).

Figure 1. Schematic overview of the motion capture recordings with regard to the ASTS.

5.1.3. Motion Capture Recordings: Apparatus and Software

The video-material was produced using a motion capture system (Optitrack™, NaturalPoint, Inc., Oregon, USA). This technique relies on the optical recording of markers placed on a subject or object. The used setup included 16 cameras and 37 markers per participant. The cameras are equipped with infrared LEDs, which emit the infrared light that is reflected by the markers and

then recorded by the cameras. Because every marker is recorded continuously by multiple cameras it is possible to reconstruct a highly precise 3D-model of the movement sequence as performed by the protagonists.

After recording, the 3D-data was processed with the help of commercially available software (MotionBuilder™, Maya™, Autodesk Inc., California, USA). This allowed us to map the human movements onto a virtual character. In our case this was done in order to minimize distraction from the displayed movements in terms of visible gender, ethnicity, age, attractiveness and other personal characteristics. For the same reason we decided to use a virtual character that looks like a wooden doll without a face in front of a black background (see Fig. 2). The use of such virtual characters has been shown to be ecologically valid (Vogele & Bente, 2010).

For the 22 included participants (reasons for exclusions, see 5.1.2.) the first five seconds of the fully developed target movements were taken as primary material to generate visual stimuli. We assumed that the intensity of the mood was most likely to be recognizable directly at the beginning of each recording. Total length of each recording was approximately 30 seconds. In each case a data set of 18 recordings was rendered and converted to AVI format for better compatibility with other software products. The software MAYA provided the positioning of a virtual camera. By this option the angle of view in respect to the virtual character's body axis could be controlled. We decided to show the participants from a 45 degree angle, because neither a full frontal perspective ("face to face") nor a 90 degree angle ("face to shoulder") seemed to fulfill the needed criteria: It was crucial that the movements could be clearly identified, which was sometimes hard from a 90 degree angle. However, it was also important to keep the movements ecologically valid, which wasn't the case for the two painting actions when displayed from a frontal perspective, because then the observer would hypothetically be looking through a transparent wall, which would be an implausible perspective. We placed two virtual cameras in each recording scene to render the material from both the left-hand 45 degree angle and the right-hand 45 degree angle. This resulted in 792 video clips (*22 Participants × 18 Recordings × 2 Camera Angles*).

The number of 792 videos allowed for a critical selection of videos for the final stimulus set in two steps: Firstly with the help of physical, objective data (5.2.) and secondly with the help of voluntary, naïve raters (5.3.).

Figure 2. The virtual character used for the stimulus production. Additionally the ROI as explained in 5.2.1. can be seen.

5.2. Kinematic Analysis

5.2.1. Kinematic Analysis: Software and Code Structure

For the objective analysis of the kinematic trajectories of the videos we used an algorithm developed in our research group (Dr. Ralf Tepest). The algorithm was implemented and executed in Matlab (R2017a). Results of the algorithm were transferred to SPSS (24) for further statistical analysis (see 5.2.2. for a description of the statistical procedure).

Basics of *motion energy analysis* (Ramseyer & Tschacher, 2011) and *motion energy detection* (Grammer, Honda, Juetten, & Schmitt, 1999) were used as inspiration for our own code. Our algorithm took AVI-files as input, which were then analyzed frame by frame as grey-scale images. The main aspects evaluated by the code were differences in pixel intensity and the size of a region of interest (ROI). The ROI was automatically defined by the amount of space that the avatar occupied per frame and can be thought of as the smallest possible rectangle encompassing the most distal parts of the body. Often this were head and feet, as well as hands, elbows or shoulders (see Fig. 2 for illustration).

We grouped our calculations and results in six main classes of values (overview of generated value classes in Table 2). As can be seen there, three of the six value classes are centered on the pixel change or grey-scale value intensities (1-3), while the other three depend on the above mentioned ROI (4-6). To simplify the comparison of the videos we implemented automated curve sketching into the code. This allowed us to easily compare the trajectories of each value over time and between videos. For example, if you think of a rhythmic movement like sweeping, then it is easy to understand that the alteration of the ROI-values changes rhythmically too. Displaying this trajectory of ROI-values as a curve allows to count the number of maxima, which can be interpreted as a measure of movement frequency or speed (see Fig. 3). In this manner we generated ten values (see Table 3) that were computed for each of the six value classes, resulting in 60 variables in total.

Table 2

Overview of Value Classes Computed by Matlab Algorithm

No. ^a	Value class	Description
1.	Amount of pixels in avatar	Number of non-black pixels in current frame
2.	Sum of intensity differences	Changes of grey-scale values across time
3.	Sum of intensity differences relative to the amount of pixels	Amount of pixels in avatar ÷ Sum of intensity differences (1.÷2.)
4.	ROI-X-Dimension	The horizontal trajectory of the movements
5.	ROI-Y-Dimension	The vertical trajectory of the movements
6.	ROI-Size	ROI-X-Dimension × ROI-Y-Dimension (4.× 5.)

Note. For each of these six classes, ten values (see Table 3) were computed, resulting in a total of 60 variables; ROI = region of interest.

^aNumbers are in Arabic to allow for logical combinations with elements of Table 3, e.g. 3V.

Table 3

Overview of Values Computed by Matlab Algorithm for Each Value Class

No. ^a	Values	Description
I.	Mean	Mean of value level (e.g. ROI-Size)
II.	SD	Standard deviation of value level (e.g. ROI-Size)
III.	n-Max	Number of maxima (for whole length of video)
IV.	n-Min	Number of minima (for whole length of video)
V.	Mean distance	Mean distance between maxima
VI.	SD distance	Standard deviation of the distance between maxima
VII.	Max. distance	Maximum distance between maxima
VIII.	Min. distance	Minimum distance between maxima
IX.	Mean amplitude	Mean amplitude (i.e. mean height difference of maxima & minima)
X.	SD amplitude	Standard deviation of the amplitude

Note. These ten values were computed for each of the six value classes (see Table 2) resulting in a total of 60 variables; ROI = region of interest.

^aNumbers are in Roman to allow for logical combinations with elements of Table 2, e.g. 3V.

The three most basic elements of each video can be defined as: (a) background, (b) signal, and (c) noise (i.e. pixel changes caused by camera- or light-irregularities). Because the noise distorts the accuracy of the signal we tested and specified two filter-variables in order to minimize this effect. Firstly, a threshold was chosen to set a minimum grey-scale value to be analyzed. Secondly, a filter value was chosen, which was used to compute a smoothed version of the original curves.

Before analyzing the data our algorithm converted the videos to grey-scale images. The minimum grey-scale value determined how much a pixel had to differ from the black background (cf. Fig. 2) in order to be analyzed. This way the noise was filtered out and the main signal remained. Threshold-values between 1 and 100 were tested prior to the main analysis. While values between 1 and 15 showed only a very subtle effect, values higher than 50 altered the distribution of the maxima and minima significantly. Thus the finally chosen value for our analytic procedure was 30. With this value it was possible to smooth the computed curve,

blocking out small alterations of the curve progression which did not reflect observable movements in the video-material.

The filter value manipulates an abstract version of the original curve (see Fig. 3). Many of the small spikes in the blue curve as seen in Fig. 3 were not visually detectable as movements when we examined the video material. For that reason we implemented this filter to compute a smoothed curve. The actual value of the filter reflects the size of the considered part of the original curve used to compute a mean curve progression. For example the filter value 1 would result in an almost identical curve as compared to the original one. Filter values between 1 and 10 were tested. Values higher than 5 resulted in very abstract curves. Values lower than 3 were very close to the original. Thus the finally chosen value for our analytic procedure was 5.

Figure 3. Example of ROI-Size alterations over time and the impact of different filter sizes.

5.2.2. Kinematic Analysis: Statistics

After computing all 60 variables for the 792 videos with the Matlab algorithm, results were transferred to SPSS for further statistical analysis: We decided to exclude all videos with outliers in any of the 60 variables (outlier defined as a value outside the range of $M \pm 2 \times SD$). To this end a z-score for each variable was computed. *t*-Tests were computed to compare different conditions (e.g. Happy and Sad). These steps were carried out in order to select those videos that showed the most homogenous features.

5.3. Perception Analysis

The Perception Analysis was conducted to compute recognition rates for both moods and actions of the videos selected via the Matlab algorithm. The 83 videos in the Perception Analysis only showed two actions (mopping, sweeping) and two moods (happy, angry). Reasons for this selection can be found in 6.1..

5.3.1. Perception Analysis: Participants

We recruited 112 volunteers (73 females, mean age = 31.66, $SD = 11.71$) via (a) mailing lists of the study programs Biology, Neuroscience, Philosophy and Psychology of the University of Cologne, (b) word of mouth or (c) a designated mailing list of volunteers of the Research Center Jülich.

Three participants participants who's answering behavior differed significantly (deviations $> 2 \times SD$) from the rest of volunteers, calculated by an index as provided by Unipark, were excluded. Additionally, it was computed how many videos per participant were not played completely. Again, participants that differed in the amount of incomplete videos more than two standard deviations were excluded ($n = 6$). Four participants were excluded, because of technical difficulties, resulting in a total remaining sample of $n = 99$.

5.3.2. Perception Analysis: Procedure

At the beginning of the survey, all participants were guided through three pages of instructions on how to participate and what to focus on. It was pointed out that all data was collected and analyzed anonymously. It was further emphasized that the task was either to focus

on the action or the mood displayed in the video. Tasks were always indicated before the start of the video and were additionally displayed above the video during playback. After the video, the next site automatically appeared and the participants had to choose between (a) mopping and (b) sweeping for the action and (a) happy and (b) angry for the mood respectively.

Each volunteer was randomly assigned to one of the four subgroups. The total amount of videos in the survey was 83. Each participant watched and rated only about a fourth of this total amount, the exact number varied between 20 and 21 in the subgroups. All videos were rated for both conditions (action and mood) within the subgroups. Meaning, in a subgroup with a total of 20 videos, all participants watched these 20 videos twice, once to rate the mood and once to rate the action. The order of the videos was randomized within the subgroups.

After completing the video rating, some basic information (age, gender, German language skills, handedness, sportiness, years of education) was assessed. On the last page followed a short debriefing, informing about the general purpose of the study and the overarching project.

5.3.3. Perception Analysis: Software

The survey was conducted via Unipark (Questback GmbH, EFS Survey, Version 10.9, <http://www.unipark.com>). Results were analyzed in SPSS (24).

5.3.4. Perception Analysis: Statistics

Two z-scores were computed for data cleansing: (a) one for the answering behavior, (b) one for the amount of incomplete videos (see 5.3.1. for details of exclusions). To compute the recognition rates, i.e. the amount of correct answers per video and per condition we computed 166 new variables ($83 \text{ videos} \times 2 \text{ conditions}$). For each of these variables we calculated the amount of correct answers relative to the total amount of answers ($\text{number of correct answers} \div \text{total number of answers}$).

6. Results

6.1. Results: Kinematic Analysis

The main goal of the Kinematic Analysis was to generate a homogenous body of videos. To this end we excluded videos that differed significantly from the mean in their psychophysical

characteristics and compared movement speed and movement energy between actions and moods. After excluding videos with outlier data in any of the 60 variables (see Table 2 and 3 for overview of computed variables) 328 of the initial 792 videos remained. The complete distribution of the remaining videos across conditions (actions, moods) can be found in Table 4. This ensured that the remaining videos were highly similar, as assessed by our Matlab algorithm.

The sad movements were excluded more often than the two others (remaining videos per mood: Sad = 99 vs. Angry = 103, Happy = 126). The two paint actions were excluded more often than the others (remaining videos per action: Paint_Brush = 37, Paint_Roller = 37 vs. Mopping = 57, Sweeping = 61, Sanding = 59, Wiping = 77). Movement speed was measured as the number of maxima of the ROI-size (hereafter referred to as n-Max-6, see 5.2.1. and Tables 2 and 3). We compared the mean n-Max-6 of the different moods across all actions (Sad $M = 6.52$ vs. Happy $M = 7.37$; Angry $M = 7.83$). There were significant differences between n-Max-6-Sad and n-Max-6-Happy, $t(223) = 3.234$, $p = .001$, as well as n-Max-6-Sad and n-Max-6-Angry, $t(200) = 5.057$, $p = .000$. But no significant difference was found between n-Max-6-Happy and n-Max-6-Angry, $t(227) = -1.790$, $p = .075$. When we compared the mean amplitude of the ROI-size (hereafter referred to as m-Ampl-6), giving us an image of the movement energy we saw no significant differences between groups (m-Ampl-6-Happy and m-Ampl-6-Angry, $t(227) = -.912$, $p = .363$; m-Ampl-6-Sad and m-Ampl-6-Happy, $t(223) = .422$, $p = .674$; m-Ampl-6-Sad and m-Ampl-6-Angry, $t(200) = 1.231$, $p = .220$).

With regard to the actions we saw the trend that the paint actions were excluded more often and in the four remaining actions we saw an uneven distribution among Sanding and Wiping (see Table 4). Additionally we found, that the movement speed of Sanding vs. Wiping differed significantly (n-Max-6-Sanding and n-Max-6-Wiping, $t(134) = 2.330$, $p = .021$), whereas there was no significant difference between Mopping vs. Sweeping (n-Max-6-Mopping and n-Max-6-Sweeping, $t(116) = -1.754$, $p = .082$). The pattern of movement is also more distinguishable between the two actions performed on the table (Sanding, Wiping), when compared to the two on the floor (Mopping, Sweeping). As confusability was one of the envisaged features of the final stimuli this made the case stronger for the two floor actions. On the basis of these results we decided to focus the following steps on a 2x2 design with the conditions being Mopping vs. Sweeping, and Happy vs. Angry. We came to this decision because the sad movements were excluded the most by the objective algorithm, but also because we found that happy movements

showed no significant difference to angry ones, as opposed to sad ones in terms of movement speed.

Table 4

Distribution of Videos After Excluding Outliers in the Kinematic Analysis

	Moods			
	Happy	Angry	Sad	Total
Actions				
Mopping	23	17	17	57
Sweeping	20	23	18	61
Paint_Roller	12	17	8	37
Paint_Brush	14	16	7	37
Sanding	27	11	21	59
Wiping	30	19	28	77
Total	126	103	99	328

Note. Paint_Roller = painting a wall with a roller; Paint_Brush = painting a wall with a brush; Sanding = sanding a piece of wood with sandpaper on a table; Wiping = wiping a table with a rag.

6.2. Results: Perception Analysis

In the Perception Analysis we brought together data from production and perception. This way we were able to infer about the personality traits and experience (immersion) of the persons producing the movements in relation to the subsequent recognition by persons perceiving these movements. For the development of the stimulus set the main goal of the Perception Analysis was to distinguish between videos that were recognizable for the displayed movement, as well as the displayed mood. First we examined the overall distribution of the videos in terms of amount of correct answers (i.e. the recognition rate). To simplify this, we divided the results into five classes according to their recognition rate (see Table 5).

Table 5

Amount of Videos Sorted by Recognition Rate

	0 – 20 %	21 – 40 %	41 – 60 %	61 – 80 %	81 – 100 %
Action	1	7	16	37	22
Mood	4	10	20	26	23

Note. The recognition rates were calculated as the amount of correct answers divided by the total amount of answers. This table includes all videos (n=83) in both conditions.

We can see in Table 5 that the distribution of the two conditions (Action, Mood) is spread in a similar fashion. Most of the videos are found in the two groups ranging from 61 – 100% in both conditions. A further examination of the relation between the two conditions revealed that 24 videos were rated for both action and mood at a rate of 70% or higher.

Additionally we examined the relations between the personal characteristics of the volunteers that participated in the motion capture recordings and the recognition rates of the videos that these volunteers produced. Specifically, we calculated correlations between personality traits (i.e. *Big Five Inventory*, *Toronto Empathy Questionnaire*, *Emotional Intelligence Scale*) and the recognition rates. With only very few low correlations with small significance we can conclude that personality traits have no considerable influence on the recognition rate of performed actions or moods. The correlation between the *Toronto Empathy Questionnaire* and the recognition rate for mood was very low and not significant, $r = -.100$, $p = .368$. So was the correlation between the *Emotional Intelligence Scale*, $r = .008$, $p = .944$. Out of the *Big Five Inventory* (BIG5) only the Neuroticism-subscale showed a significant correlation with the recognition rate for mood, $r = .222$, $p = .043$ (see Table 6 for other results of this calculation).

Following up on the scarce available studies that examined personality traits and movement kinematics (Luck et al., 2009), we assessed the correlation between the subscores of the BIG5 and the already introduced n-Max-6 as a measure of movement speed. Again no significant correlations were found (see Table 7).

Lastly, we computed the correlations between the subjective immersion of the volunteers (*How well could you immerse into the mood?*) and the subsequent recognition rates. As can be seen in Table 8, there is a significant correlation between each of the three immersion ratings and the subsequent recognition of the mood, but not the recognition of the action.

Table 6

Correlations of Personality Traits and Recognition Rates

	1	2	3	4	5	6	7
1 RR_Mood							
2 RR_Action	-.088						
3 BIG5_1	.100	-.051					
4 BIG5_2	-.203	-.112	.306**				
5 BIG5_3	-.164	-.166	.294**	.305**			
6 BIG5_4	.222*	-.020	-.273*	-.316**	.196		
7 BIG5_5	-.009	-.185	.099	.531**	.363**	.070	

Note. RR_Mood = Recognition rate for mood; RR_Action = Recognition rate for action; BIG5_1 = Extraversion; BIG5_2 = Agreeableness; BIG5_3 = Conscientiousness; BIG5_4 = Neuroticism; BIG5_5 = Openness.

* $p < .05$. ** $p < .01$.

Table 7

Correlations of Personality Traits and Movement Speed

	1	2	3	4	5	6
1 n-Max-6						
2 BIG5_1	-.108					
3 BIG5_2	.185	.306**				
4 BIG5_3	.180	.294**				
5 BIG5_4	-.071	-.273*	-.316**	.196		
6 BIG5_5	-.024	.099	.531**	.363**	.070	

Note. N-Max-6 = Number of maxima of the ROI-size (see 5.2.1.); BIG5_1 = Extraversion; BIG5_2 = Agreeableness; BIG5_3 = Conscientiousness; BIG5_4 = Neuroticism; BIG5_5 = Openness.

* $p < .05$. ** $p < .01$.

Table 8

Correlations of Immersion into Mood and Recognition Rates

	1	2	3	4	5
1 RR_Mood					
2 RR_Action	-.088				
3 Immersion_Happy ^a	.327**	.023			
4 Immersion_Sad ^a	.315**	-.080	.672**		
5 Immersion_Angry ^a	.249*	.019	.433**	.277*	

Note. RR_Mood = Recognition rate for mood; RR_Action = Recognition rate for action;

^aAfter each recording block the participants indicated whether they were able to immerse into the demanded mood via a Likert scale (details for the procedure, see 5.1.2.).

* $p < .05$. ** $p < .01$.

7. Discussion

7.1. Discussion: Production

We started our study with six different everyday movements (see Table 1), which we first examined with the help of an algorithm to find differences in the kinematic properties. To select a homogenous set of videos from all recordings, we excluded videos that showed outlier data in any of the computed variables (see 5.2.). Especially videos of the two painting movements were excluded by this measure in many cases. The amount of remaining videos for these two conditions was too low to create a stimulus set from and thus we decided to exclude all painting videos from further processing. Further exclusions were based on movement speed comparisons between moods. As expected, the sad movements were performed significantly slower than both happy and angry movements. On the other hand, when comparing Happy and Angry we found no significant difference in movement speed or movement energy. This led to the exclusion of all sad movements.

We furthermore compared the mean movement speed of the different actions and found a significant difference between Sanding and Wiping. This is objective finding is intuitively comprehensible, because sanding a piece of wood with sandpaper generally occurs with a higher

pace (i.e. faster back-and-forth movements) than wiping a table with a rag. However, no difference was found between Mopping and Sweeping, thus Sanding and Wiping were excluded.

To summarize, the above mentioned exclusions led to the selection of two actions (Mopping, Sweeping) and two moods (Happy, Angry) for further processing. This was based on the dispassionate algorithm and statistical measures (excluding outliers). On the basis of these facts we were able to select a homogenous set of videos in terms of physical characteristics. Later, this will be of the utmost importance in the fMRI study, because the goal of the latter is to compare the brain activation resulting from the viewing of the videos across conditions. We can now argue that the objective psychophysical characteristics of these videos are highly similar. In the next section we sum up another important characteristic of the stimulus material, namely the homogenous recognition rate.

7.2. Discussion: Perception

With the help of an online study, we were able to separate videos that are easy to recognize from those who are not. For each video we computed the recognition rates for actions and moods based on the ratings of naïve volunteers. The majority of videos were rated above chance level, ranging from 60 – 100% correctness. It should be noticed, this doesn't mean that a video is rated equally for both conditions. So for the final stimulus set we will select videos that show similar recognition rates for both mood and action. In other words, the recognition rates for both conditions will be highly similar. The final selection of videos for the fMRI study is currently pending and cannot be included in this report (but see 9. for general remarks on this matter).

7.3. Discussion: Interrelations of Production & Perception

When bringing together the data of the movement production (personal characteristics and experience of volunteers during motion capture recordings) and movement perception (recognition rates of movements for actions and moods) we established two important findings: (a) The relation of personality traits and the subsequent recognition rate of movements, and (b) the relation between subjective immersion into a mood and the subsequent recognition rate of this mood.

The psychological traits of the participants that volunteered for the motion capture recordings and the subsequent recognition rates showed no considerable significant correlations. This

included a Big-Five Inventory, a scale for emotional intelligence and one for empathy (see 5.1.2. for details). This suggests that humans seem to be able to recognize movements and moods on a nonverbal level independently of the personality of the observed individual. Being able to infer about the inner state of various different personality types is crucial in everyday life. The people we meet show vast differences in their personalities, but still we are able to interact with them and also infer about their inner states by interpreting their nonverbal behavior.

Luck et al. (2009) measured low, but significant correlations between BIG5-subscales and movement trajectories. The authors point out that their small sample size and the fact that most of the correlations did not reach significance should be taken into consideration when interpreting the results. Following up on this, we computed correlations between the BIG5 and movement speed, but found no correlations.

Our data suggests that neither emotional intelligence nor empathy is correlated with the ability of expressing moods through nonverbal behavior. In future studies it would be therefore interesting to reproduce similar experimental setups with autistic individuals. ASD is associated with lower scores on both empathy (Baron-Cohen & Wheelwright, 2004; Rogers, Dziobek, Hassenstab, Wolf, & Convit, 2007) and emotional intelligence measurements (Brady et al., 2014; Petrides, Hudry, Michalaria, Swami, & Sevdalis, 2011). Comparing the resulting recognition rates of movements performed by autistic persons with those of a control group could be of high interest for the research in nonverbal communication in ASD.

Furthermore, we found a significant correlation between the subjective immersion into the three moods and the subsequent recognition rate for mood. This finding seems plausible as it seems trivial. Still, the connection between people stating they immersed into a mood very well and the subsequent recognition of that mood is not self-evident and here we provide proof with our data. In everyday life, when we want to communicate a mood or other emotional content nonverbally we are intuitively able to do so. Now, we can add to this statement that the level of immersion into a mood is likely to have an impact on the subsequent recognition rate.

To the best of our knowledge this has been the first time that the subjective experience during movement production and the subsequent recognition rates have been examined together. Other studies in similar contexts either did not assess the experience of the persons during movement production (Atkinson, Dittrich, Gemmell, & Young, 2004; Montepare, Goldstein, & Clausen, 1987; Wallbott, 1998) or did not correlate this experience during production with the movement

perception during observation (Michalak et al., 2009). Interestingly, the recognition rate for the actions did not correlate with above mentioned subjective immersion. This can be interpreted as a hint indicating two distinct underlying systems: one for the recognition of actions and one for the recognition of moods. This could be validated by a study with autistic persons, who show impaired sensitivity to nonverbal cues (Senju et al., 2009). A systematic comparison of movements produced by persons with and without ASD that would subsequently be rated by persons with and without ASD would allow for a 2x2 design and potentially a double dissociation to further corroborate these first indications of two distinct underlying processes.

8. Conclusions: Production and Perception of Whole-Body Movements

In this study we examined the production and perception of everyday movements. The overarching project will continue to use the generated stimuli to probe the social brain. Additionally to deriving a highly robust stimulus set, we showed (a) the independence of personal characteristics from subsequent recognition of mood and action when expressed through nonverbal behaviour, and (b) the correlation of subjective immersion into a mood and subsequent recognition of this mood. Future perspectives for corroborating studies are discussed above (7.3.).

9. Future Directions: Probing the Social Brain

Why all this work to produce stimuli for an fMRI study? The answer is: control for confounding factors. With all steps outlined above, we established a set of videos that are highly homogenous in terms of recognition rates and psychophysical features. Both of these features will allow for a very differentiated examination of the two brain networks (MNS and MENT) that the fMRI study will be focused on. Across the two conditions (MNS: action vs. MENT: mood) the exact same videos will be shown: once associated with the question *What action was performed?*, and once associated with the question *Which mood was the person in?*. Within the conditions, the psychophysical features (luminance, pixel change, movement trajectories) will be highly similar across videos, because our kinematic analysis allowed excluding videos exhibiting outlier data (see 5.2.). The similar recognition rates across the two conditions imply a similar

level of difficulty. This is especially important for an fMRI-paradigm, since tasks that are too easy would generate the possibility of mind-wandering. This phenomenon is also called daydreaming or stimulus-independent thought (Antrobus, Singer, Goldstein, & Fortgang, 1970; Singer, 1966; for a meta-analysis, see Fox, Spreng, Ellamil, Andrews-Hanna, & Christoff, 2015) and has been linked to the activation of the so-called *default mode network* (Raichle et al., 2001) that overlaps with MENT (Mars et al., 2012). In other words, if a task is too easy, it bears the risk of false-positive MENT-activity.

The exact choice of videos for the final stimulus set is currently under discussion. After the set has been put together the next step will be to test these videos in a behavioral study with the same experimental paradigm that will be used in the final fMRI study. Then the fMRI experiment can take place. Hopefully we will be able to enrich the scientific community with this new approach and the resulting data soon.

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12. Declaration of Authorship

I am aware of and understand the University's policy on plagiarism and I certify that this thesis is my own work, except where indicated by referencing, and that I have followed good academic practices.

Signed,

Sebastian Lammers, July 2017

13. Conflict of Interest

The author has no conflict of interest to declare.