Posture Shifts in Conversation: An Exploratory Study with Textile Sensors

Sophie Skach
Human Interaction Lab
Cognitive Science Research Group
Queen Mary University of London
s.skach@qmul.ac.uk

Patrick G.T. Healey
Human Interaction Lab
Cognitive Science Research Group
Queen Mary University of London
p.healey@qmul.ac.uk

Abstract

Posture shifts involving movement of half or more of the body are one of the most conspicuous non-verbal events in conversation. Despite this we know less about what these movements signal about the interaction than we do about smaller scale movements such as nods and gestures. This paper reports an exploratory study of posture shifts in seated conversation. Using data from video analysis and bespoke pressure sensors in clothing, we are able to distinguish different types of posture shifts and detect them in speakers and listeners. The results show that large scale posture shifts are performed by both speaker and listener, appear to be distinct from smaller movements associated with preparing to speak and that the posture shifts associated with speech offset are less clearly defined. We discuss the potential of using pressure sensors to investigate these salient conversational states.

1 Introduction

One of the most salient body movements people make in natural conversation is a general posture shift in which most or all of the body goes through a momentary adjustment. While these movements could, of course, be explained by fatigue or physical discomfort there is also an intuition that they have communicative significance. Unlike, say, iconic gestures or nods that accompany each utterance these are relatively global, infrequent movements that seem to mark larger conversational units or signal something about participant's stance towards an issue. Scheflen (1964) was one of the first to document these moments in detailed case studies of psychotherapy sessions. He defined posture shifts as movements involving at least half the body and proposed that they are organised around changes in *position* or point of view.

Others have since elaborated on Scheflen's findings, describing posture shifts as self synchronised movements to speaker turns (Condon and Ogston, 1966), as signals for different levels of engagement in a conversation (Schegloff, 1998) or to correlate with tonic stress (Bull and Connelly, 1985). In most cases, postural changes are linked to speaker behaviours. They can accentuate it in fine grained ways (Ekman and Friesen, 1969), and also accompany the change of speech categories (Bull and Brown, 1977). Posture shifts can also appear outside of speech and may be interesting signals in interaction in their own right. For example Bull has considered frequent posture changes as a marker of boredom (Bull, 2016).

Although there is an intuition that posture shifts are important non-verbal signals, not least because of their relative scale, the literature on them is limited. More attention has been given to posture as a static feature of participation in conversation, especially in relation to posture matching as indication of affiliation or attraction (Beattie and Beattie, 1981; Bianchi-Berthouze et al., 2006; Mehrabian, 1969), and in their spatial formation (Kendon, 1976).

The work on posture reviewed above relies on video combined with human coded judgements of posture type for analysis. More recently there has been an increase of interest in the use of motion capture and markerless computer vision techniques as ways of automatically measuring posture (Wei et al., 2016). Here we extend this to considering the use of pressure sensors as a way of sensing changes in seated postures. This has the advantage that it is not susceptible to problems with occlusion that can affect camera-based techniques (e.g. see Tan et al. (2001), Meyer et al. (2010) and Skach et al. (2017)). It can also detect subtle changes in pressure that do not necessarily translate to overt visual cues. Furthermore, we introduce pressure sensors made of conductive textiles integrated into fabric surfaces as a method to capture shifts in movement and behavioural cues. We use bespoke 'smart' trousers with an integrated sensor matrix to record pressure data around the thighs and the buttocks. This is used in an exploratory study of changes of posture both for listeners and speakers in multiparty seated conversations. We explore the potential of pressure sensors in trousers to detect changes of state in the conversation and discuss the qualitative characteristics of some of the events they detect.

2 Background

There are several suggestions as to what postural shifts mean and what role they play in punctuating communication between interactants, between speakers and addressees, and also when in conversation they are most likely to appear. Generally, posture shifts have been associated with changes in topic ("locution cluster", coined by Kendon (1970)) or situations (Gumperz, 1982). Condon (1976) and Lafrance (1976) also reported on postural synchrony, leading to higher rapport, or if incongruent, are indicators for negative relations between people (Lafrance and Broadbent, 1976). Furthermore, the exposure and intensity of such movement may present cues to interpersonal relationships. For example, Wiemann et al. (1975) suggested that the more familiar interactants are with each other, the more subtle the postural shifts and bodily movement, moving parts of limbs (fingers) rather than entire body parts. This can be linked to Kendon's observation (1972) that generally, those body parts are in more motion than the torso and the legs.

2.1 Speakers and Listeners

Postural changes have been reported most commonly in connection to speaker behaviours, or listeners' perception of speakers. Hadar (1984) reports that they appear primarily at the start of a speaking turn, when the interactant changes their state from listener to speaker, or after a long speaker pause.

Speakers are said to punctuate the end of their turn and maintain a more upright posture overall, leaning rather forward than backwards (Wiemann and Knapp, 1975), or emphasise words and phrases. Even micro-movements like facial expressions, e.g. raising an eyebrow, can be in line with changes in tonality, e.g. lowering voice (Condon and Ogston, 1966). Bull and Brown (1985) identified 3 postures related to the upper body and 5 related to the lower body, evaluating them in relation to 6 different categories of speech.

Listeners' postures are examined less often. It is suggested that the status of an addressee can be interpreted by the openness of their legs and arms (Mehrabian, 1968), and that listeners synchronise with speakers (Condon and Ogston, 1966) and shared postures between them are linked to a high rapport (Lafrance and Broadbent, 1976). Also pauses between speech as listener turns are associated with postural adjustments by Hadar et al. (1984).

2.2 Sensing Social Cues

Sensing bodily movement as behavioural or affective signals has been subject to numerous human-centred research, both for interaction with each other or with a device (HCI). While conventionally, video and audio recordings were used, other modalities have been explored in more recent years. One of the goals for new technologies is to maintain an undisturbed environment, deploying sensors unintrusively. Ambient interior design and the utilisation of everyday objects has been successful a contribution to such ubiquitous computing (see e.g. Vinciarelli et al. (2009) or Venkatnarayan and Shahzad (2018)).

A material that is closest to our skin, follows our movements organically and is a natural interface we have used for thousands of years is fabric. Therefore, using our own clothing as a sensing surface seems appropriate to capture bodily actions and behaviours (such as in Mattmann et al. (2007)).

Here, we exploit trousers and test their performance to capture postural shifts as dynamic movements as opposed to static postures, which we have proven to reliably identify with sensing trousers before (Skach et al., 2018).

3 Methodology

In this section, we report on the design of the 'smart' trousers and the development of custom-made textile sensors, as well as on the process of collecting video data in a user study.

The data is drawn from a corpus of seated, three-way unscripted conversations (Figure 1). The conversations were video recorded to allow

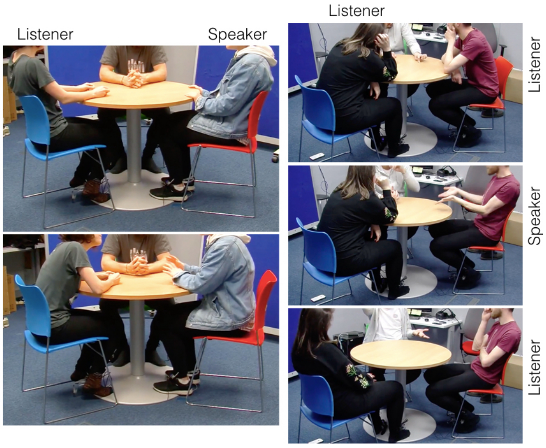

Figure 1: Examples of postural shifts, to be read from top to bottom: Left: Listener leans towards speaker, responds to their posture change (leaning forward). Right: Listener posture shifts on the left; postural transitions from listener to speaker and back, on the right.

for hand coding of non-verbal behaviours using two cameras from different angles to reduce problems with occlusion. In addition, participants wore specially constructed trousers with an array of fabric pressure sensors built in (see below) to detect lower body movements. These sensing trousers continuously recorded changes of pressure across thighs and buttocks.

This combination makes it possible to identify conversational phenomena such as speaking or listening and identify whether they are systematically associated with lower body movements.

3.1 Textile Sensors in Trousers

A fabric sensor matrix of 10x10 data points was designed (adapted from Donneaud and Strohmeier (2017)) and embedded in custom made stretch trousers, as seen in Figure 1. Each leg's matrix therefore consists of 100 sensors and is deployed around the upper leg, covering the area from the knee upwards to the buttocks in the back and the crotch in the front, as illustrated in Figure 2. Placement, shape, amount and type of the sensors, as well as the type of trousers that were chosen for the sensor integration derived from ethnographic observations of multi-party social interactions. The use of soft, textile conductive materials, of which the pressure sensors consist, enables unintrusive sensing without augmenting conventional trousers' properties. A detailed documentation of the design and manufacturing process of this wearable sensing system is reported in (Skach et al., 2018).

Tier	Description
Talk	on- and offset of overt speech
Pre-Speech	2 sec immediately before talk
Post-Speech	2 sec immediately after talk
Posture Shift	gross movement of torso & legs

Table 1: Overview of the hand coded annotations in Elan

3.2 Data Collection

3.2.1 Participants

A total of 42 participants were grouped into 14 three-way conversations, each of them was given a pair of sensing trousers[1]. A subset of 5 participants were annotated and analysed here: 4 female, 1 male. These participants were selected randomly from a predetermined subset of participants that performed above average in preliminary posture classification tasks.

3.2.2 Procedure

Participants were seated on a round table and given the task to resolve a moral dilemma between them. Conversations lasted 15 to 20 minutes and were captured from two angles with video cameras in addition to recording the pressure data from the sensing trousers that each participant was wearing during the entire time of the recording.

3.2.3 Sensor Data Processing

The pressure readings from the fabric sensors were recorded with a time stamp and were stored on a microSD card integrated and hidden in the hem of the trousers. The data was captured at 4Hz by a microcontroller placed in the hem, too. For further processing, the data of each of the 200 sensors was normalised.

3.3 Annotations

The recorded videos were hand coded using the software package Elan (Brugman and Russel, 2004), with two annotators for determining speech, and one annotator to code posture shifts.

First pass coding focused on overt speech with starts and ends of annotations defined by onset and offset of audible speech. Second pass annotation then coded the moments immediately before and after speaking arbitrarily defined as 2 sec-

[1]We manufactured multiple trousers in different sizes (Small, Medium, Large) to accommodate all participants.

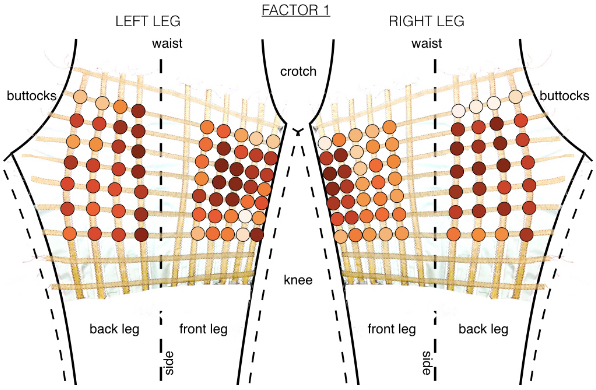

Figure 2: Visualisation of component 1 for each sensor, mainly discriminating posture shifts, talk, and pre-speech movement. Dark colours show positive associations, bright tones negatives (similar to a heat map).

onds just before, and 2 seconds just after speech. These were coded regardless of other non-verbal behaviours or marked bodily movement. Third pass coding was used to identify posture shifts defined as gross body movement involving either or both, the upper and the lower body. This includes leaning forwards, backwards, and sidewards, but also performing leg crossing and adjusting sitting position with thighs and hips (shifting the weight within a seated counterpose). Both, speaker and listener posture shifts were included. Again, some movement coincided with other behavioural cues, verbal and non-verbal. An overview of the coding scheme can be seen in Table 1.

Later, the annotations were synchronised with the sensor data of both legs by merging and approximating the time lines of both recordings with each other. Broken sensors were removed from further processing and analysis.

4 Results

The results are reported in two steps: a) analysis of the pressure sensor data and b) observations of the interactional context of the posture shifts.

Across all participants in our video, posture shifts occurred on a regular basis. In a time window of 15 minutes, an average of 35 posture shifts were annotated, which equates to 2-3 posture shifts each minute. By posture shift, we define the positional movement of the torso and / or the lower body including the legs. In the scope of this work, we exclude gaze and gestures from postural shifts, but acknowledge that gestures in particular are often described as part of a postural shift that affects the dynamics of the entire torso

Comp.	Total	% of Variance	Cumulative in %
1	38.182	30.303	30.303
2	31.003	24.606	54.909
3	25.184	19.988	74.896
4	9.523	7.558	82.454
5	6.491	5.152	87.606
6	3.624	2.876	90.482
7	1.994	1.583	92.065
8	1.575	1.250	93.315
9	1.218	0.966	94.218

Table 2: Varience Explained (Extraction Sums of Squares Loadings)

(Cassell et al., 2001).

4.1 Posture Shifts and Pressure Changes

4.1.1 Factor Analysis

The 200 pressure sensors on each participant (100 right leg, 100 left leg) produce a relatively complex array of pressure measurements with a significant amount of redundancy between sensors. Hardware failures reduced this to 165. If a sensor failed on one participant the data were deleted for all participants to ensure equivalent sensor arrays were used for each person. The sensors yielded a total of 6278 pressure measurements across the whole sample (in total for both legs, per participant). In order to reduce the complexity of the sensor data a factor analysis was calculated using SPSS (v.25). This yielded 9 components that account for 94% of the variance.

The influence of the four coded behaviours listed in Table 1 on pressure changes was analysed using Automatic Linear Modelling with forward stepwise model selection. Talk (1/0), Beforetalk (1/0), Aftertalk (1/0), and Participant (1-5) were used as predictors and the regression factor score for each component from the factor analysis for each pressure observation as the target.

For Component 1 the model fit is 88%, Information Criterion -10,438. The analysis shows that Participant ($p < 0.000$), Postureshift (Coefficient = -0.133 $p = 0.003$), Talk (Coefficient = -0.047, $p < 0.000$) and Beforetalk (Coefficient = -0.041 $p < 0.004$) predict changes in first factor (component) of the pressure data. The effect of the individual sensors for component 1 are visualised in Figure 2, showing which sensors have positive and negative associations. From this, we see that the front mid thigh on the left leg, and the mid buttocks of the right leg affect the predictions most positively, while the sensors in crotch proximity, on the upper buttocks, as well as on lower mid thighs have negative associations. Interestingly, these patterns are not symmetrical.

The estimated means of these effects for Factor 1 are illustrated in Figure 3. Components 2-8 are primarily predicted by Participant with different Components picking out different subgroups of participants. There are two exceptions: Component 3 is also marginally predicted by Aftertalk (Coefficient -0.031, $p < 0.000$) and Component 6 is also predicted by Postureshift. Component 9 which has a relatively poor model fit (4.5% accuracy, and Information Criterion -216.0) is predicted by Postureshift (Coefficient = -0.204, $p < 0.000$), Aftertalk (Coefficient = 0.125, $p = 0.001$) and Beforetalk (Coefficient = 0.101 $p < 0.005$).

The pressure data changes corresponding to the predictors found for Component 1 are illustrated in Figures 4, 5 and 6. Note that, in effect 'Beforetalk' is the inverse of Talk but sampled over a smaller data set. Together they show that talking is associated with an overall increase in lower body pressure (when seated) and that the shift takes place in a two second window prior to speaking. Conversely, large scale posture shifts are associated with an overall decrease in lower body pressure.

Overall, these preliminary results suggest that the array of pressure sensors can be used to discriminate between global posture shifts and also the movements people make immediately before and after speaking. This replicates an earlier analysis of the pressure data comparing talking vs. listening using machine learning techniques. The results also highlight the substantial individual variation in the pattern of the pressure data. Individual identities form the largest and most consistent predictor of pressure patterns across all the analyses.

4.2 Observational Findings

The posture shifts coded from the videos were explored to develop hypotheses about the possible functions of the large scale posture shifts in this corpus. We divide types of posture shifts according to the time of their appearance in relation to overt speech: before, during, after and between speakers' turns.

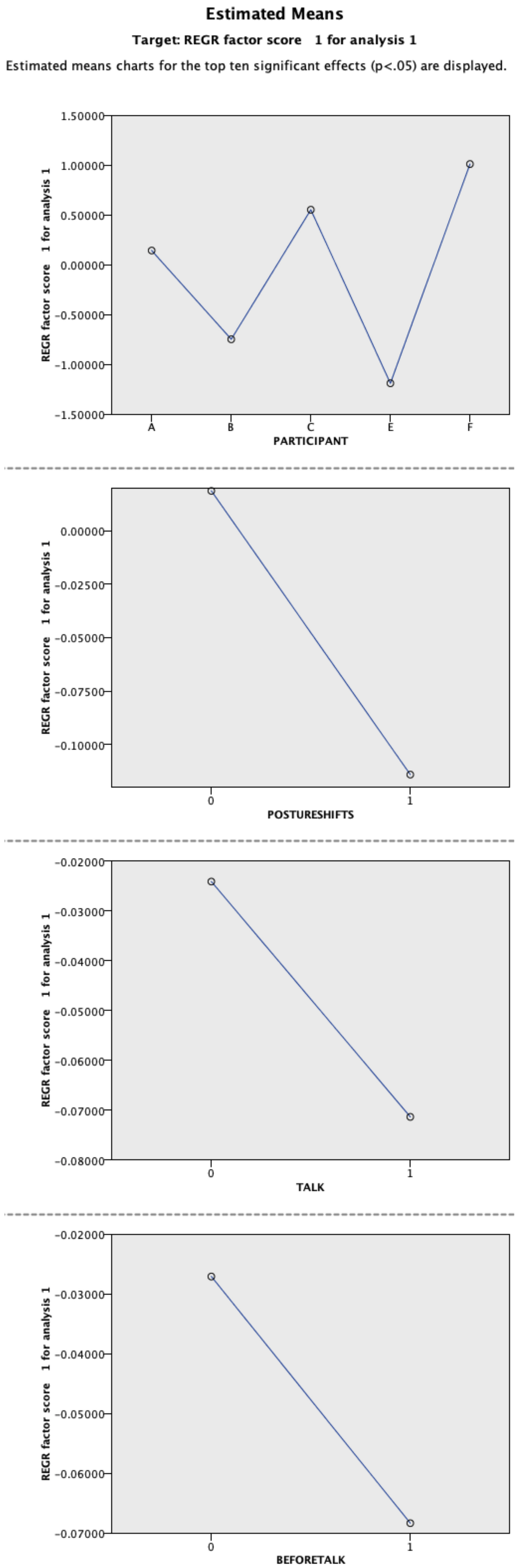

Figure 3: Estimated Means of the first factor for the top ten significant effects ($p < 0.05$) are displayed

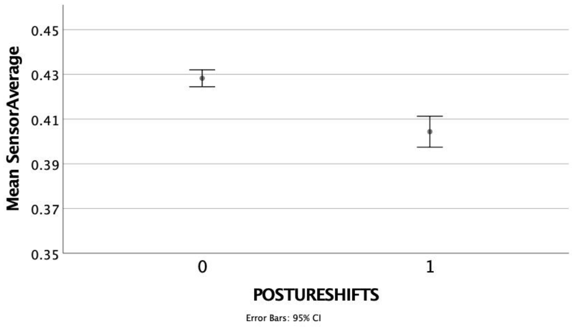

Figure 4: Pressure Change with Posture Shifts: Average Normalised Sensor Data

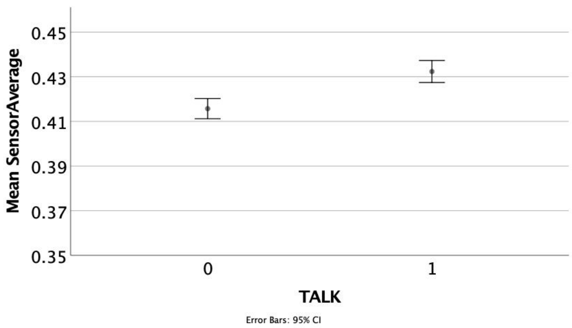

Figure 5: Pressure Change when Talking: Average Normalised Sensor Data

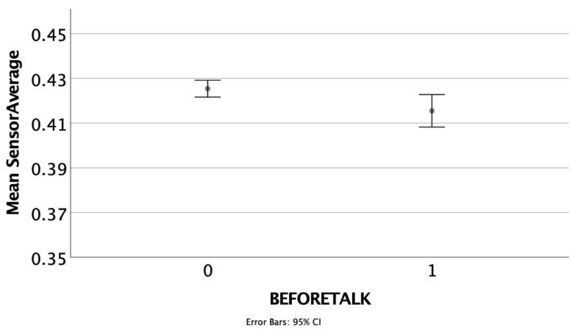

Figure 6: Pressure Change Before talking: Average Normalised Sensor Data

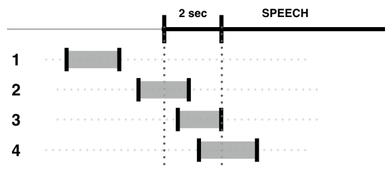

Figure 7: Preparatory Movement Types: 1) performed several seconds before utterance; 2) completion within 2 sec before talk; 3) start & end within 2 sec window;, completion often precisely at start of talk; 4) start within 2 sec window, overlap with talk.

4.2.1 Preparatory Movement

Listed below are the four categories of posture shifts before a speaker's turn, also illustrated in Figure 7:

1. Start and end of movement several seconds before utterance (end of movement ≥2 sec before talk), however still close enough to be seen as preparatory.

2. Start of movement before speech, outside of 2 sec window, but completion within this time window, up to the very start (onset) of speech.

3. Occurrence of posture shift precisely within 2 seconds before speech, ending at the very start of utterance.

4. Posture shift starts within 2 sec just before, and is executed and completed during speech

The evaluation of the sample set of 5 participants shows that, considering the frequency of these categories, 80% of preparatory postural movements can be captured in part or as a whole through the time window of the 2 seconds annotations. The rest of preparatory posture shifts happens largely between 4 and 3 seconds before speech. One approach therefore, with the aim of capturing these movements, is to extend the specified time window to 4 seconds before talk. This, however, would often mean that postural preparation is longer than talk itself, whose duration is 3.21 seconds on average across all participants. These findings confirm our initial hypothesis on posture as preparation for speech, and also align with previous suggestions that posture change indicates turn taking and interactants signal their next speaking turn through these movements.

4.2.2 Delayed Post-Speech Shifts

We observed that postural shifts that are not classified as preparatory movement, but rather as post-speech movement, follow a different pattern. Overall, they occur less frequently and are only rarely performed in the immediate aftermath of talking utterances (inside the 2 seconds time frame). This is not to say they don't exist, but more commonly, they seem to be performed with a short delay. We can categorise this delay in similar ways as the preparatory movement (mirroring Figure 7):

1. overlap with speech: posture adjustment performed towards the end of speech and beyond: start of movement within speech, completion after speech has ended.

2. no delay: start of postural movement immediately after offset of speech

3. short delay: after utterance ends, postural shift is performed with a delay of $\leq$ 2 sec (within the specified time window)

4. long delay: considered as a movement being performed more than 2 sec after speech has ended (outside specified time window)

In numbers, we have found that only 2 out of 47 post-speech movements are performed immediately at the offset of speech. Most postural shifts that are associated with the end of an utterance are performed with a delay between 1 and 4 seconds after talking (with rare outliers up to 5 seconds after, everything later than this was not linked as a post-speech postural adjustment) - with 49% of them falling into the specified time window of 2 seconds post talk. In fact, most movements of this category started within this time window, but at the same time, 28% of posture shifts started only clearly after 2 seconds post speech. In other words, this means categories 3) and 4) are the most common amongst post-talk postural movement - with a short or long delay.

4.2.3 Active Listener Postures

Although postural adjustments have been closely linked to speaking, they are interesting phenomena in their own rights. In our data set, speakers' shifts only account for 40.44% of posture shifts. Listeners' posture shifts, however, often co-occur with other conversational behaviours, appearing to signal something about participants' relation to what is happening in an interaction. We observed that in most cases where not linked to speaker behaviour, they are often related to specific 'active' listener signals, such as nodding , backchanneling or laughing, which go somewhat beyond these specific forms of concurrent feedback. Two examples are depicted in Figure 1. In some cases, shifts in postures seem to predict these behaviours, too, similar to the patterns of preparatory movement for talk. In general, the movement patterns for backchannels were most similar to the ones for talk. During nodding, the movement of both torso and legs appeared visibly more subtle and was observed to only become more embodied when close (within 5 seconds) to a speaking turn. This could be discussed as another extended preparation for speech, too. However, posture shifts related to nodding only make up 6.56%, the smallest category. When looking at laughter, postural movement was expectedly the most marked and obvious, and also forms the second largest set of all posture shifts, 28.96%. In comparison, 8.20% of all postural movements relate to backchannels. Additionally, our observations suggest that not only during these active listener behaviours, but also for the embodied transition from inattentive to attentive listeners, postural shifts play an important role, accounting for 17.76% of all movements, and expanding on the reports of Kendon (1972), Scheflen (1964) and Blom and Gumperz (1982).

5 Discussion

The results of this exploratory study suggest that posture shifts are a significant and rich interactional phenomenon that deserve more attention. Nonetheless, it is important to acknowledge that the data set presented here is small and the observations made here can only be considered preliminary.

5.1 Topic Changes in Speech

Kendon (1972) has discussed posture shifts in relation to changes in topics, and Bull and Brown (1985) have also noted different postural patterns in specific categories of speech (e.g. drawing back legs or raising a foot during a statement). In this work, we have not considered differences in what is being said, but have treated talk as a broad, overt event. Posture shifts performed during speech were coded and included in the analysis, but were not further divided into more fine grained categories of nuanced speech. Therefore, we did not examine whether postural movement during a speaker turn correlates with topic changes. From observation, however, it is suggested that in some occasions, there is evidence to confirm the works of Kendon, Cassell (2001), Schulman (2011) and others. For example, the participants of our sample set that have embodied such topic changes in a marked way, have moved both their torso and lower body significantly. Following this, it would be interesting to explore whether different markedness of posture shifts correlate with different conversational events not only in individual cases, but in a general conversational structure.

5.2 Individual Variation

The most obvious point about the data presented here is the large amounts of individual variation. Individual participants showed patterns of movement that seemed specific to them, and may be a starting point towards an approach to identify individuals through postural movement. Nonetheless, the analysis suggests that there are still commonalities in the patterns of posture change that may generalise across individuals.

In consideration of individual variation, there were some nuances in postural movements we observed that were distinct for different participants. Rhythmic, continuous events were leg bouncing and back- and forwards swinging with the torso. These events occurred alongside other, previously mentioned behaviours that present more specified social signals and are to find for each participant: nodding and laughter. In some cases, they also appeared to correlate with affective states. One participant, for example, bounced their leg in supposedly uncomfortable moments. Another participant, when listening and not giving any other cues to speakers, continuously moved his torso back and forth, lightly swinging. Others have performed smaller movements like fidgeting more frequent than gross postural shifts.

5.3 Familiarity and Synchrony

The idea that interactants move in different ways depending on how familiar they are with each other comes from Wiemann and Knapp (1975), and suggests more subtle movement when participants know each other. This aligns with the works of Kendon (1976), discussing spatial organisation as a signifier for interpersonal relationships. We have noted this phenomenon in individual cases and have not gathered enough evidence to support Wiemann and Knapp's suggestion in full, but have observed that the number of gross body movements decreased after the first 5 minutes into the conversation. After that, movements became more subtle. In this context, it is also to note that the participants we have grouped together, were in different personal relationships: some knew each other briefly, while others were not familiar with each other at all.

Furthermore, it is also not clear and has not been investigated in this study, whether posture shifts are always noticed by conversation partners.This especially refers to smaller scale movements, whose interactional relevance could followingly be discussed, too.

5.4 Handedness and 'Footedness'?

One additional suggestion emerging from this study is that the pressure sensors of the left leg appear to be more discriminative of posture shifts than the right leg. This might have two reasons: the variation of the sensor performance, considering self made sensors as difficult to calibrate; or a potential correlation with handedness. There are some indications that people gesture differently with their dominant hand we speculate that this might also influence the pressure distribution of legs, too. To elaborate on these ideas, more information about the participants is required, that was not asked for in our studies.

6 Conclusion

This exploratory study contributes to the discourse on the meaning of posture shifts and their role in conversation. We have showed that it is possible to identify different types of postural movements through a novel multimodal approach: video recordings and a wearable sensing system made of fabric pressure sensors in trousers. These were used for a study in which we recorded the data of three-way conversations. The results show that there is a lot to draw from posture shifts in general, in relation to speech, as well as to active listener behaviours, verbal and non-verbal, and that smart clothing can be used to detect them.

7 Acknowledgements

This research is funded by the EPSRC and AHRC Centre for Doctoral Training in Media and Arts Technology (EP/L01632X/1). We thank all participants and colleagues for their support - in particular Tom Gurion for his help with data formatting.

References

Geoffrey W Beattie and Carol A Beattie. 1981. Postural congruence in a naturalistic setting. *Semiotica*, 35(1-2):41–56.

N Bianchi-Berthouze, Paul Cairns, Anna Cox, Charlene Jennett, and Ww Kim. 2006. On Posture as a Modality for Expressing and Recognizing Emotions. *Emotion in HCI workshop at BCS HCI*, pages 74–80.

Hennie Brugman and Albert Russel. 2004. Annotating multi-media/multi-modal resources with ELAN. *International Conference on Language Resources and Evaluation*, pages 2065–2068.

P. E. Bull and R. Brown. 1977. The role of postural change in dyadic conversations. *British Journal of Social and Clinical Psychology*, 16(1):29–33.

Peter Bull and Gerry Connelly. 1985. Body movement and emphasis in speech. *Journal of Nonverbal Behavior*, 9(3):169–187.

Peter E Bull. 2016. *Posture & gesture*, volume 16. Elsevier.

Justine Cassell, Yukiko I Nakano, Timothy W Bickmore, Candace L Sidner, and Charles Rich. 2001. Non-Verbal Cues for Discourse Structure. In *Proceedings of the 39th Annual Meeting on Association for Computational Linguistics*, pages 114–123. Association for Computational Linguistics.

William S. Condon. 1976. An Analysis of Behavioral Organization. *Sign Language Studies*, 13:285–318.

William S Condon and William D Ogston. 1966. Sound film analysis of normal and pathological behavior patterns. *Journal of nervous and mental disease*.

Maurin Donneaud and Paul Strohmeier. 2017. Designing a Multi-Touch eTextile for Music Performances. In *Proceedings of the 17th International Conference on New Interfaces for Musical Expression (NIME17)*, pages 15–19, Aalborg, Denmark.

Paul Ekman and Wallace V Friesen. 1969. The Repertoire of Nonverbal Behavior: Categories, Origins, Usage, and Coding, Semiotical.

John J. Gumperz. 1982. *Discourse Strategies.* Cambridge University Press.

U. Hadar, T. J. Steiner, E. C. Grant, and F. Clifford Rose. 1984. The timing of shifts of head postures during conservation. *Human Movement Science*, 3(3):237–245.

Adam Kendon. 1970. Movement coordination in social interaction: Some examples described. *Acta psychologica*, 32:101–125.

Adam Kendon. 1972. Some relationships between body motion and speech. *Studies in dyadic communication*, 7(177):90.

Adam Kendon. 1976. Spatial organization in social encounters: The F-formation system. *Man Environment Systems*, 6:291–296.

Marianne Lafrance and Maida Broadbent. 1976. Group Rapport : Posture Sharing as a Nonverbal Indicator. *Group & Organizations Studies*, 1(3):328–333.

Corinne Mattmann, Oliver Amft, Holger Harms, Gerhard Tröster, and Frank Clemens. 2007. Recognizing upper body postures using textile strain sensors. *Proceedings - International Symposium on Wearable Computers, ISWC*, (2007):29–36.

Albert Mehrabian. 1968. Relationship of attitude to seated posture, orientation, and distance. *Journal of Personality and Social Psychology*, 10(1):26–30.

Albert Mehrabian. 1969. Significance of posture and position in the communication of attitude and status relationships. *Psychological Bulletin*, 71(5):359–372.

Jan Meyer, Bert Arnrich, Johannes Schumm, and Gerhard Troster. 2010. Design and modeling of a textile pressure sensor for sitting posture classification. *IEEE Sensors Journal*, 10(8):1391–1398.

Albert E Scheflen. 1964. The Significance of Posture in Communication Systems. *Psychiatry*, 27(4):316–331.

Emanuel Schegloff. 1998. Body torque. *Social Research*, 65(3):535–596.

Daniel Schulman and Timothy Bickmore. 2011. Posture, relationship, and discourse structure: Models of nonverbal behavior for long-term interaction. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 6895 LNAI:106–112.

Sophie Skach, Patrick G T Healey, and Rebecca Stewart. 2017. Talking Through Your Arse: Sensing Conversation with Seat Covers. In *Proceedings of the 39th Annual Meeting of the Cognitive Science Society*, London.

Sophie Skach, Rebecca Stewart, and Patrick G T Healey. 2018. Smart Arse: Posture Classification with Textile Sensors in Trousers. *Proceedings of the 20th ACM International Conference on Multimodal Interaction*, pages 116–124.

Hong Z. Tan, Lynne A. Slivovsky, and Alex Pentland. 2001. A sensing chair using pressure distribution sensors. *IEEE/ASME Transactions on Mechatronics*, 6(3):261–268.

Raghav H. Venkatnarayan and Muhammad Shahzad. 2018. Gesture Recognition Using Ambient Light. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 2(1):1–28.

Alessandro Vinciarelli, Maja Pantic, and Herv Bourlard. 2009. Social signal processing: Survey of an emerging domain. *Image and Vision Computing*, 27(12):1743–1759.

Shih-En Wei, Varun Ramakrishna, Takeo Kanade, and Yaser Sheikh. 2016. Convolutional Pose Machines. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.

John M. Wiemann and Mark L. Knapp. 1975. Turntaking in Conversations. *Journal of Communication*, 25(2):75–92.