Student motion and it's potential as a classroom performance metric

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Abstract. Can we predict students attention from a classroom video? We present our system for analysing movement of students in classroom during a lecture. We go into details about the technical side for analysing motion of people with limited visibility, and we present preliminary results which show how the neighbourhood and location in the classroom affect individual movement.

Keywords: classroom, orchestration, motion, attention, location

1 Introduction

A major difference between a novice and experienced lecturer is how they adjust their presentation to the audience [3]. A whole body of work on orchestration [6][7] is dedicated to helping teachers perform well in the classroom by helping them become a reflective practitioner [16]. But how is the teacher to judge the effect of his lecture on an unfamiliar group of listeners?

Our system analyses the behaviour of audience of the classroom [17]. To present motion as a valid indicator of audience response, we draw a parallel with previous works on studying interaction between students in the classroom, and show how our method relates to previous findings while remaining unobtrusive to the learning process.

1.1 Theoretical Background

Literature which focuses on teacher behaviour is rich. From practical advice [5] to detailed analysis of teacher's usage of space [15], the importance of teachers role in the process of learning has been re-confirmed throughout the literature [8][11]. The theory of orchestration [6][7] which formulates the presentation of knowledge as only one of the many duties of the teacher attempts to demonstrate the many facets of teaching process. An equally important question about the state of the classroom audience - the students - was discussed from a number of sides: modelling student goals [2], how the group behaviour is affecting the students [9], how relevant is the position of the student [13] and how it affects interaction [1]. Also, general studies on behaviour in groups provide us with useful concepts of audience inhibition, diffusion of responsibility [14] and social loafing [10] which can also be observed in a typical classroom.

In this paper we focus on social influence in the audience (e.g. that people look at others for guidance [14]) and how the position of a person in the classroom is affecting his or hers behaviour in terms of motion. The conclusions previously stated in [1] and [13] show the effect of classroom location in terms of verbal activity and participation. Inspired by the concepts of unobtrusive measurements [19], we are evaluating how these conclusions can be supported by the new measurement of body motion in the classroom.

2 Method

2.1 Motion Analysis

Analysis of the motion is based on tracking feature points in the video [4]. Our setup consists of three cameras used for coverage of the students and one observing the teachers actions. Initial steps of analysis - synchronization of video streams from all sources and annotating visible regions in which students reside during the lecture, are described in [17].

Our main challenges in the process of extracting a measurement of motion for further analysis were *i)* inter-personal occlusions, *ii)* perspective distortion, *iii)* normalization of the amount of movement recorded from a single person into a comparable measurement between several persons.

a) b) c)

Fig. 1. Motion grouping. **a)** Individual motion vectors shown as purple arrows **b)** Grouped motion into motion tracks **c)** Marked student areas and centres of Gaussian probabilities of each student

***i*) Inter-personal occlusions** are handled by taking several pre-processing steps before assigning the motion to a person. The main idea is that by grouping the motion vectors into motion tracks, we can more reliably assign the whole track to a single person, instead of taking each motion vector as an isolated measurement.

Steps of the process are illustrated in Figure 1. Raw motion vectors are shown in Fig.1a as purple arrows who's intensities add to the amount of motion of one person at one time instance. Motion vectors (v) are next grouped into tracks (T) which consist of "cloud" of motion vectors over several frames. The criteria for grouping is based on proximity, direction similarity and intensity of the vectors. For visualisation purposes, a set of cloud centres from several frames are connected into a track which is shown in Fig.1b. Finally the entire track is assigned to the student of highest probability (g_f) (principle can be formalized as $g_f = \arg\max_g \sum_{\forall v \in T} p(v|g)$). Each student ($g$) has a Gaussian distribution centred on the position of his head (depicted in Fig.1c). The entire track is assessed over every center (i.e. student) and motion is assigned to the student with the highest probability. Fitting the Gaussian distributions produced regions in which a motion vector will be assigned to a specific person.

In cases where a student was occluded on more than 80% of tracked area the movements were undistinguishable from the person in front of him/her. Depending on the quality of the measurements for the person in front, either one or both students were removed from further processing.

Taking into account that our primary interest was motion between neighbours, it is important to notice that this method was designed so that *i)* a motion occurring between two students would not be assigned to both students *ii)* large motions spanning several tracked areas would be assigned to a single person, and not to a group of people.

***ii*) Perspective distortion** To compensate for the perspective effect, the number of points remains constant over all annotated tracked areas. Also, the intensity of the vector is normalized by the diagonal of the student region.

***iii*) Normalizing the amount of motion** Normalizing the motion of a person has proven to be difficult. We based our normalization on two premises *i)* student is on average sitting still during the class *ii)* student has at least one full-body movement in the recorded footage (e.g. pose shift). To scale this to a range of 0-100% motion, we take the median value of movement intensity as the 5% motion (which corresponds to small motion/sitting still being registered as 5% motion), and we verify that given this basic motion intensity the student reaches 100% motion at least once during the class. Motion which registers above the threshold of 100% is clipped to the maximum value.

The final motion intensity over time can be visualized as shown in Figure 2b.

2.2 Procedure

We base our results on analysis of two classes, described in Table 1. The teachers were two experienced lecturers. The lectures were given in different times of the day - one being in the morning, the other in the late afternoon time, and in different rooms. We observed each lecture for the duration of 45 minutes

Class no.	Class size	Analysed	Female ratio	Rows	No. of benches
1	38	29	36.8%	6	7
2	18	14	22.2%	4	5

Table 1. Basic information about analysed classes

with 4 interruptions. During this time at a random interval (average duration 10 minutes) the students filled out a questionnaire sampling their activities. We are aware that our request from the students to fill out the questionnaire about attention interrupts their work, so the interruption was treated as a simulated synchronised activity and marked as a "question-asked" period. Activities during those periods were not taken into consideration when analysing student behaviour.

Even though we initially consider both classes comparable, small number of students in the second classroom rendered conclusions from that observation statistically invalid. We did use it to show that there is a consistent trend in both cases.

A major influence on the behaviour of students in the classrooms plays the geometry of the arrangement [18] which differs in the two cases. Since the geometry of the room changes the student's perception of the speaker, due to proxemics, we decided against normalizing the space in the way it was done for [1], which would make the two classes comparable.

3 Observations

We compared the number of synchronized movements during the class period. Synchronized movement is considered in a dyadic context, and is in this case defined as body movement with more than 30% intensity from each of the two persons being compared. Persons can move at the precisely same moment or within the range of ±4 seconds from each other, in which case the person who moves first has to be visible to the second person, and is considered as the stimulus.

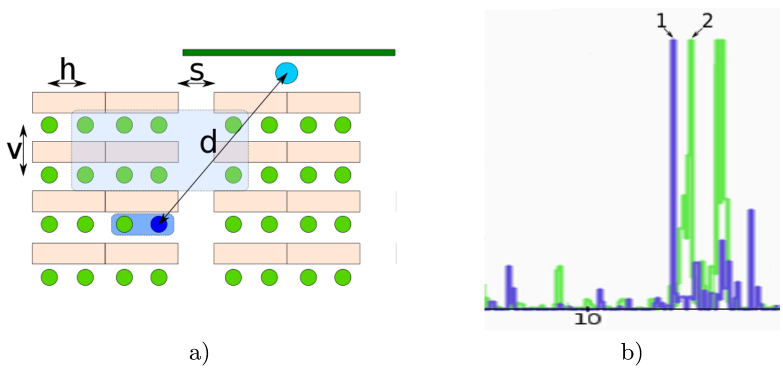
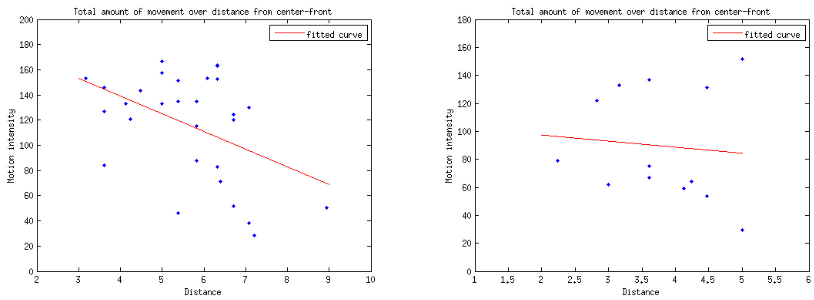


Fig. 2. ***a)*** Organization of classroom zones and units of measurements, top of the image represents the front of the classroom. **v,h** - vertical and horizontal spacing between students, 1 *uod* (unit of distance) in our current setup. **s** - between-row spacing, 1 *uod*. **d** - distance between the professor (center-front of the classroom) and the analysed student. Light-blue zone represents the visible students for student at the location 3rd row, 4th seat. Darker-blue rectangle around the student represents his immediate neighbourhood. ***b)*** Example of co-movement on a movement intensity graphic of two persons. Student 1 shifted hers seating position (blue line), 2 seconds later, neighbouring student 2 (marked in green) also started re-adjusting herself.

We compared the average number of synced movements between pairs sitting immediately next to each other (marked as the dark-blue region in Fig.2a) or not.

The null hypothesis can be rejected with a two-sampled t-test ($p \leq 0.05$). Neighbouring pairs had higher probability of synchronized moving (First class: $\mu = 76.54, \sigma = 32.47$; Second class: $\mu = 63.33, \sigma = 24.33$), than a randomly picked pair (First class: $\mu = 54.43, \sigma = 15.6492$; Second class: $\mu = 44.88, \sigma = 18.42$). We also noticed no significant difference in number of synchronized moments between the pair from a visible student population (marked as the light-blue region in Fig 2a) and the rest of the student population.

We also tested the influence of teachers proximity to the movement of the students: the further away students are from the front-center of the classroom (the point which is the closest to the teacher in both cases, represented as measurement d in Fig 2a) the less active they are (Kendall correlation is -0.284 ($p = 0.03$) for Class 1; for Class 2 is -0.172 ($p = 0.45$)). The distance measurement is approximate, and is using 1 unit of distance (uod) per row and seat difference (passages between rows are taken into consideration also as 1 uod). Because of the small sample we used Kendall correlation for analysing the samples and we have seen the same trend in both cases (Figure 3), even tough the correlation was insignificant for the second classroom.



a) b)

Fig. 3. Correlation between distance from teacher and motion intensity in classes 1 and 2. **a)** Class 1. 28 students in sample. Kendall correlation -0.284 ($p = 0.03$) **b)** Class 2. 13 students in sample. Kendall correlation -0.172 ($p = 0.45$)

4 Conclusion

We have shown interesting correlations of movement with previous work on position and class activity from [1] and [13]. We see the teacher and the teaching material as the dominant "signal" in the classroom. With our conclusion that students are most likely to "sync" with the person next to them, we show that it is not the only relevant signal, and that the immediate neighbourhood also has a significant influence on students attention, and also on students in-class performance.

In our future work we would like to explore further the phenomenon which we call the "distraction ripples" - assuming the transitivity of the motion-syncing, we would like to capture the spreading of influence of one class-member to people around him. We are also interested to correlate how well do these "ripples" spread in high-attention and low-attention groups of students, in order to make a new metric of class attention. We feel that the future reflective practitioners would benefit from a system that will provide an objective metric of performance. We see the system as being especially useful for novice teachers who might be primed to see cooperative students [12].

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