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REFLECTIONS ON ALGORITHMIC THINKING FOR VIDEO ANALYSIS – SORTING OUT COMPLEX HUMAN ACTIVITIES

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ABSTRACT. Algorithmic thinking approaches utilize a number of steps to break down the issues surrounding a given problem. It involves a problem being analyzed and specified to then identify basic actions to the given problem that can be used to construct an algorithm. This means that algorithmic thinking is a very structured way of thinking and analyzing things. In this article, I will discuss how those principles could be used in teaching video ethnography, how to think analytically in a field that is inherently qualitative and descriptive in nature. Utilizing examples from a video ethnography course, it is explained how students examine video data that was collected as part of their inquiries about the nature of scientific practices. The process of using an algorithmic structured analysis in their examinations allowed the students to identify the materiality of scientific activities. The process also allowed for the identification of rules, explained through the use of ethnomethodologically inspired methods. The students examined visual and non-verbal aspects. Through this process, the students were able to identify basic actions and examine the relationship between tools, rules, practices and people. It's argued that repurposing the concept of algorithmic thinking for the analysis of complex events can prove to be useful for teaching, since a structured analytical approach permits for organized and critical examinations of human practices.

Keywords: video ethnography; algorithmic thinking; basic actions

Introduction

Analyzing videos that capture the complexity of humans interacting with each other, materials and artefacts can be a challenge. This is due to the richness and complexity of information that is being captured. However, just like other scientific investigations, video analysis is about a systematic study of video involving the encoding and decoding of information. In this

article, I will argue that video analysis requires forms of algorithmic thinking that may include the use of particular laboratory techniques or technological tools; the use of specialized language, or conventions that also shape how findings and information is being communicated and shared. This implies that the particular methods chosen shape the way how the overall scientific goal for knowledge generation through and with video including the control of particular variables in video analysis can be achieved.

Human activities can appear unpredictable, so ethnographic or anthropological researchers task themselves with the systematic study of people and their cultures, not necessarily to predict but to find explanations and patterns of behavior (Wolcott, 1999). Recently it has become popular to utilize video in pursuit of such aims since video allows for the capture of interactions between people and the world. The simple fact that video recorded information can be scrutinized to reveal delicate and easy to miss details, and to be viewed again and again, makes it a useful data collection tool.

Qualitative studies and the way how information is analyzed, presented and used to make generalizations about human interaction have been criticized since they do not necessarily produce representative data or enhance their reliability through the setting of advanced criteria (Katz, 2015). It is not surprising that the systematic study of human behavior seems like an overwhelming task, particularly when students are facing initially unstructured data that leaves them feeling uncertain how and where to start their analysis. This article will discuss the practical encounters and analytical challenges to do with video ethnography to show that one way of breaking down complex encounters is through the identification of basic structures. I will use examples from a course on video ethnography for techno-anthropologists where students had the task to analyze visual data they collected about science –technology practices. However, before discussing the details of my examples, I will first elaborate on where I see an intersection between the analytical demands of video ethnography and algorithmic thinking.

Connecting Video Ethnography and Algorithmic Thinking: A Matter of Definition

How can the term algorithmic thinking be connected with, and be of any use to thinking about, the analysis of ethnographic video? This may be a perhaps puzzling proposition since algorithmic thinking is often discussed in

relation to mathematics, computer science or informatics where algorithms, or rules organized in calculations or computable operations are used to analyze and specify problems. Under such paradigms algorithms are constructed by identifying basic actions that can be used to automatically solve problems and may also involve that such actions are identified across similar cases, in order to identify and refine an algorithm (Futschek, 2006). The key relevance to video analysis is the breaking down of complex captured activity into simple repeatable functions. In the case of video analysis, it could mean to tag via mouse click in a video when a person moves forward, which when repeated is consistently enough and may indeed show patterns that can be connected with other patterns that have slightly different functions. The grouping of the functions is the algorithm.

However, in this article I am not necessarily interested in exploring how to create algorithms for video ethnography but what it means to apply algorithmic thinking. Since the systematic study of interactions through video requires making particular analytical choices I want to explore here if the concept of algorithmic thinking can be repurposed to acquire meaning for the analysis processes in video ethnography. To do this I will use Gerald Futschek's (2006, p. 160) categorization of algorithmic thinking, which he describes as:

- the ability to analyze given problems
- the ability to specify a problem precisely
- the ability to find the basic actions that are adequate to the given problem
- the ability to construct a correct algorithm to a given problem using the basic actions
- the ability to think about all possible special and normal cases of a problem
- the ability to improve the efficiency of an algorithm.

This suggests that algorithmic thinking is the analytical approach to achieve a particular outcome through a careful selection of methods or protocols. Jeanette Wing (2008) writes that: "An algorithm is an abstraction of a step-by-step procedure for taking input and producing some desired output." In contrast computational thinking, which is an often-connected concept, has a focus on data and the interpretation or transformation of data with the help of a computer. Computational thinking is the automation of abstract thinking through a machine (Wing, 2008).

Brennan and Resnick (2012) who were working with the Scratch software to teach young children computational thinking present seven concepts needed to produce an algorithm: sequences, loops, parallelism,

events, conditionals, operators, and data. Sequence signifies how individual steps or activities come together to form an action. Loops are repeatable actions. Events are the signifiers that cause things to happen. Parallelism refers to the fact that typically multiple sequences of instructions happen at the same time. Conditionals indicate that some events only take place under certain circumstances. Operators are computational support for mathematical or logical expressions, and finally data is all about the storage, retrieval and use of selected values.

In this article, I will use examples from an undergraduate techno-anthropology course to explore Futschek's as well as Brennan and Resnick's (2012) concepts closer, to see if they can be applied to video analysis. Before that I present some background to video studies.

The Power of Video Analysis in Ethnographic Studies

Ethnographic research is concerned with making sense of the realities that are experienced by people in the world. There are, of course, differences between the varying ethnographic forms of studies. Taking ethnomethodology as an example, George Psathas (1980) explains that it is about understanding processes rather than identifying facts to reveal changing social creations. This leaves the question on how to identify such processes and whether the principles of algorithmic thinking can be applied to the analysis of ethnographic video?

A way forward is to identify the affordances of video. Video recordings have the big advantage that they capture close-to-reality episodes that can be revisited. I deliberately refer to close-to-reality since true objectivity through video is compromised simply by whoever made a decision to position a camera and frame what was being captured, since even very basic recording decisions, such as the positioning and framing of cameras, shape the 'lens' on reality (Robben, 2007). However, due to its permanency, video creates opportunities for systematic scientific observations through careful, precise, and consistent analyses to produce explanations of diverse and complex activities (Klette, 2010). Taken this way, video opens up opportunities to explore the complex dimensions of materiality, embodiment, time, space and multimodality simply because it captures visual and audible events as they occur. In this way video ethnography is significantly different to ethnographies without video that are based on the records captured through field notes of an observer and his or her subjectivity. Once recorded on

video, different aspects that can be captured can be examined and re-examined to figure out underlying basic actions.

Scrutinizing the micro details that can be identified in video data has been utilized for example by those studying human ethology. With interests in evolutionary and adaptive aspects of human behavior video microanalysis has provided to ethologists with new and interesting insights for example into mother-infant interactions (Beebe, 2014). Beebe's work foregrounds also how video shaped her own behavior and the relationship between her and her participants, when they were watching videos for analysis together. Another example of video microanalysis comes from ethnographic examinations of interactions that take place in school settings. Elmesky, for example (2015), utilized video microanalysis to study the interactions between teachers and students in a high-school chemistry class, also to view the video together with his informants. Elmesky's work showed the power of video analysis to capture moments that teachers made unconsciously and that created different responses from individual students. The analysis allowed the researcher to identify and isolate different interactive moves that were then strategically used back in class. This means that the analysis of video was used to identify basic elements of interactions that could then be reapplied and tested.

Video analysis has also been used for the analysis of discourse and the study of grammar, where words, sounds, meaning, and the order of words in sentences is examined in much detail. An example of linguistic video microanalysis is the work of Marjorie and Charles Goodwin, both who are known for their research in embodied communication. Both researchers are linguistic anthropologists and not only take an account of the discourse, but they examine the pitch and intonation patterns of the people they observe, and compare and connect them with body postures and body alignments (Goodwin, 2000; Goodwin and Goodwin, 2000). Through the use of conversation analysis, pitch analysis and notation of body orientation in space they break down complex human interactions to identify how emotions can be detected through embodied stance (Goodwin, Cekaite and Goodwin, 2012). This is not necessarily done to predict but to interpret what has been witnessed.

In the process of unpacking video recorded events, it is not unusual that researchers adopt new language to 'make the familiar strange'. Goodwin, Cekaite and Goodwin (2012) refer for example in their detailed analysis of embodiment to congruent or discordant body alignments to unpack the complexity of emotions as they play out between people. They transform videos into line drawings that are annotated with arrows and lines. The

seeming distortion allows to zoom in or out to of a complex moment in time to break down the *problematique* of understanding people's interactions. The adoption of new language, symbols and signs allow the researchers to break down observations into smaller units and identify basic building blocks that help to create an understanding of people engaging with each other or things. In his article 'Disassembling the classroom', Tobias Roehl (2012) focuses in his analysis of video on the role materials play to expand video analysis from people to materials and their role as objects of knowledge and how they shape the unfolding of people's interactions.

The process of breaking down complexity in video ethnography by reducing data allows for an analysis at a micro level. This process includes also establishing links between other data, to justify the relationship between data collected in different media (for example video, audio, photos and field notes), and identify ways to transcribe or represent the analysis of dynamic visual data for research dissemination (Aarsand and Forsberg, 2010).

Not surprisingly, video based data collection has become a popular choice in ethnographic studies including behavioral, educational, anthropological, social science and related research (Alrø and Dirckinck-Holmfelt, 1997; Jordan and Henderson 1995). While video analysis has been used for some time now, it's only in the recent past that researchers have learned to scrutinize video data in more systematic ways, with the aim to develop coding schemes that are robust enough to allow for 'replications and comparisons' across different contexts (Klette, 2009, p. 71).

It has thus become a methodological choice to use video for the study of people in their environments and how they interact with each other and the materials they utilize.

To exemplify the notion on algorithmic thinking for ethnographic video analysis, I am presenting the case of students' learning to systematically observe scientific and technological practices with the help of video. The context and details of the case will be presented next.

Background to the Example

The data stems from a 5th semester course in techno-anthropology. Students are educated to utilize ethnographic-anthropological methods and approaches to study and examine the intersection between people and technology, both as users and as designers of technology. The semester course introduced the students to the big ideas about the nature of science and technology before pairing them for a week with scientists and engineers,

to accompany them one-on-one, collect video data to explore the nature of their work, and to compare the students' assessment with normative descriptions about the nature of scientific or engineering practices they were taught earlier. They were tasked to collect video footage and then break it down utilizing theoretical frameworks of their choice, to explain the nature of scientific work practices. The video footage was combined with additional ethnographic material they collected.

Here is an excerpt from one of the student's accounts of his data collection:

Data collection in-situ:

I am following the practical work Eva (the scientist) does (video recorded).

I talk with her (audio recorded).

I ask her questions about what she is doing and what's going to happen.

I keep written notes and jottings so I can remember what has happened, about what she's doing and what she explains.

I write my notes on paper, the computer and phone. When there was time I sat with my computer and wrote notes and when we 'worked' I wrote on the phone.

At the same time, I took pictures of her work with a video camera.

Video shadowing tools:

Phone, video camera.

Taken pictures of her when she tries to identify a problem and find a solution.

I have covered when she analyzed the data.

Interviews:

I ask her who she is and about her background?

What is she doing (referring to my observations)?

I talk to her use of models?

Environment where my observations take place:

Lab / Office / and in spaces that are intermediate zones for having meals or coffee

I take note of her use of language in respect to the environment

(Martin's notes)

Students and scientists were asked for their consent to utilize the data that is shared in this article. Pseudonyms are used in all examples to protect individual identities. This course was set in a problem based learning

environment where students practice and apply how to work with problem scenarios, throughout their education.

Video to Analyze a Given Problem (Analysis and Specification)

While this may seem at first an easy enough task, it is not necessarily easy to accomplish. From the outset, the problem was to understand the nature of scientific work practices. To define the details of their problem in the context within which students were doing their investigations, the students' video recorded their impressions of the practices 'their' scientist was working within. After their week in the field they returned with stories, in the form of a variety of recordings and field notes. From an initially broad problem formulation to identify the nature of scientific practice through videos, students had to focus on the particular and nested aspects of the scientific work practices they observed. The videos helped them to identify what aspects they could analyze in detail, since it depended on the activities they had been able to cover. The students worked with individuals in different departments in the faculty of engineering and science, but after their week in the field the class came together and viewed each other's videos and listened to each other's reflections to identify routines and practices.

The following two figures (1 and 2) were still images the students posted as part of their problem analysis process. Lars was intrigued by the way how 'his' scientist seemed to think in and through models. He referred to his video footage to point out that every time Lars asked the scientist about his work he showed him a model.

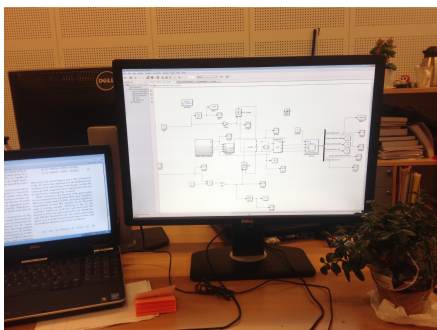


Figure 1: Computer modeling, testing through models

While Martin identified the role that creativity and spontaneity played in the way a scientist thinks and works. He referred to an incident where the scientist connected a game controller unit in an experimental set up.



Figure 2: Using a game controller in an experimental set up

In both cases, as well as the examples by the rest of the class, their close inspection of the video footage they brought back from the field helped them to define the specificity of their problem. As a result, students' problem formulations were further advanced by for example asking; *what role does modeling play in shaping the nature of a scientist's work?* This refinement led the students to identifying several intermediate steps: A categorization of the range of incidents where their scientist was referring to or using models, including: for supporting information retrieval, information input, information computation and information visualization and communication for the scientists. A similar process applied to the other students.

Video to Find the Basic Actions that Are Adequate to the Given Problem

Lene was interested in 'her' scientist's use of technical equipment and how this shaped the nature of his work. She decided to use Activity Theory (Kaptelinin and Nardi, 2006) as her analytical framework to understand the relationship between how technical equipment mediated the scientist's activities. The framework required Lene to go through the following steps: break down the activities she captured into smaller units, identify the motives of activities, categorize any underpinning rules, and find any characteristics of the community these activities were set in. This process meant that she had to identify the basic components of her problem formulation, in the context of the processes that she observed. Peter Denning (2010) explains that 'to think computationally is to interpret a

problem as an information process and then seek to discover an algorithmic solution' (p. 371).

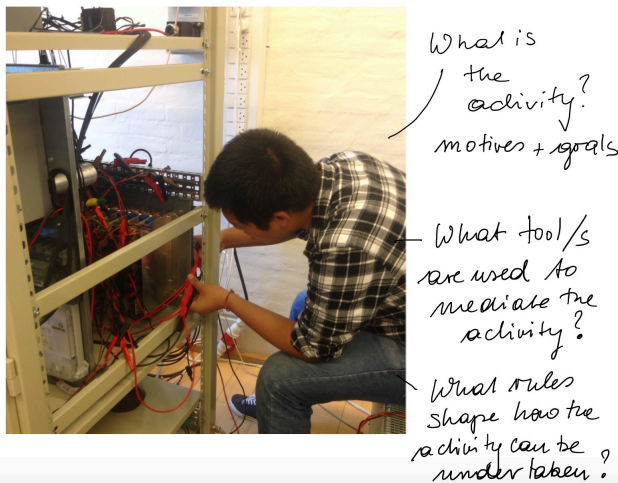


Figure 3: Unpacking scientific activities

In discussions, we identified the different aspects she had to examine closer (see figure 3), bearing in mind that her observations were set in a particular context. In a way, the student had to deconstruct their videos into smaller units in order to put them back together into a filmed sequence of events. This highlighted also causal relationships to the students.

The Construction of an Algorithm to a Given Problem Using the Basic Actions

The students in this course were tasked to reduce the complexity of what they witnessed to some key statements or basic actions. The process to get to those key statements can be exemplified through Martin's interest and unpacking of the role of creativity:

Scientists design interventions

The design process requires imagination

Imagination is a creative process

Imagination starts with a thought

Creative imaginations are key aspects to scientific work.

(From Martin's presentation made in class)

Martin achieved this analysis by identifying episodes in his video that signified creative imaginations in scientific work.

He selected the following image to make his point:



Figure 4: A creative solution for the ElectrosSpinner

In each of those episodes he was able to identify basic building blocks that had a causal relationship (similar to Brennan and Resnick's (2012) conditionals). By breaking his observations down into different basic blocks, Martin identified that *imagination* is a key aspect to scientific work and that it typically starts with a thought. He analyzed his video to search for episodes of creative imagination to then break those down in his video footage. Here he had to review and test his assumptions, also since he needed to be able to re-identify those aspects in the videos. The other students were able to identify similar steps, including: Scientific observations cannot always be done directly; Indirect way of doing observations is facilitated through tools; Tools facilitate the generation of data; Data drive models that record observations. The video ethnography 'algorithms' that were constructed did not feed into an automated system that would then scan the video data to produce quantifiable data, but they could have, since the students used the transcription software Elan that they used to code their videos. However, thinking algorithmically, in the sense that they systematically analyzed their videos helped the students to organize their data and this contributed to the production of knowledge about complex systems.

Video to Think about Special and Normal Cases of a Problem and Improve the Efficiency of an Algorithm

When the students returned from the field, they were sharing and jointly viewing video data in data sessions (see for example Fraser et al., 2005). During data sessions, several students viewed each other's video data to jointly examine and give feedback on the analysis that had been produced thus far. This gave the students an opportunity to review their selections and themes and zoom in on key interactions or components they had identified to adjust them further if needed. To examine some of their assumptions on a micro-level they utilized tools such as pitch analysis to identify where they could see clear indications where their participant scientists added emphasis highlighting emotional dimensions to what they explained on video to refine their analysis.

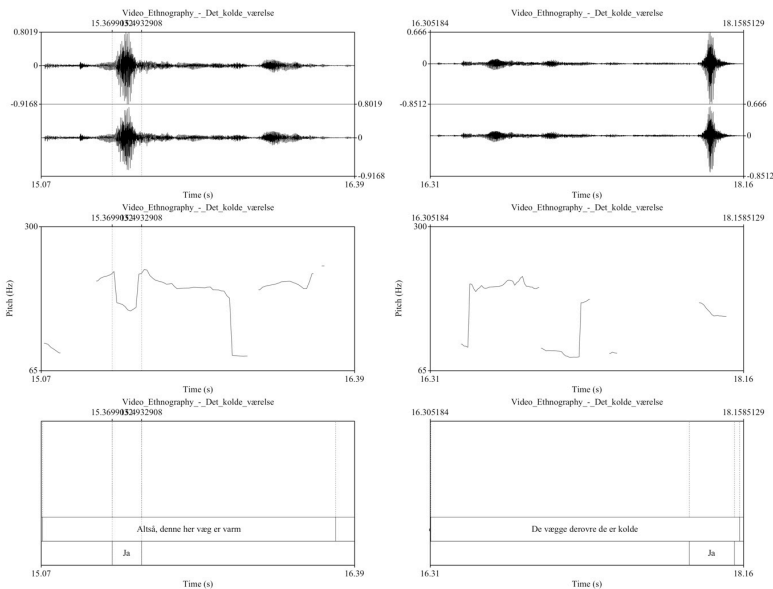


Figure 5: Pitch analysis of statement:
This wall is warm and that one is cold

Students were able to identify emotional arousal as coding category to their video analysis which they also applied to the protocols of other video analyses, such as when they were analyzing video interviews.

Focusing on small details, such as prosodic analysis (pitch and volume), helped the students in justifying and refining their arguments during the data session. The joint discussion of their problem analysis is also a common

practice in the way students engage in problem based learning activities. Typically, half way through their semester work student groups come together in a status seminar to listen to each other's work and give each other feedback. This means the process of the data sessions aligned with the established practices in this study environment. The students realized also that the video data bound them to concentrate on what had been captured. They also realized that this meant that not always had they managed to capture all of the information they may have needed, thus the video identified also clear boundaries as to what this source of information afforded to the students and what it didn't.

Discussion

This article was not a presentation on video analysis, but rather an argument on how to foreground and detail the systematic thinking approach needed to understand, profile and predict people's practices captured on video and to explore if the tenets of algorithmic thinking could be repurposed for this pursuit. Since video data collection captures large amount of naturalistic information it is an important step for the researcher to reduce this complexity, also since this allows the researcher to focus on small details that can then be magnified through the analysis process. This detailing of small details allows for the identification of sequences and series of steps (Brennan and Resnick, 2012). For instance, Lene's analysis of the scientist's modus of working showed the connections and sequential steps between materials and ways of how they mediated operations in this environment. The reduction process typically involves that the researcher focuses on details that have been recorded to examine them in more detail and magnify them. This looping of sequences (Brennan and Resnick, 2012) was evident in the repeated examination of pitch analysis to identify coding categories to be applied as part of wider coding protocols. This was also the task that the students in this course had to face. They had to learn that while video seems a tempting tool for data collection in ethnographic studies a researcher can be easily overwhelmed by the complexity of information, while trying to address the richness that plays out in real situations. Reductionist perspectives (established through dense coding of data) may be contrasted to more open methods that allow that various complex information to come together. The analysis of the micro-nuances of social relationships may include kinesics, proxemics, prosodics and other situated parameters of

human interaction (Goodwin, Cekaite, and Goodwin, 2012). Connecting back to Parisi's (2016) advice on utilising the physical materialities to structure analysis it can be argued that the video data represented those materialities. The video data was collected as part of the students' ethnographic inquiries and revealed its materiality through the structured analysis process. This materiality allowed for the identification and emergence of rules that the students explained.

The students were able to identify some basic patterns not only by analyzing ethnomethodologically what was said and discussed (Garfinkel, 1994) but also by focusing on non-verbal aspects (Jordan and Henderson, 1995). Taking note of physical, semiotic, and logical orders helped the students to account for the development of interpretations and by focusing on basic actions, they utilised an algorithmic thinking approach to video ethnography. This was meant to help to explore what is beyond the scope of discourse to highlight the materiality of the things people use or interact with and how they sense and experience the world.

Conclusion

It is not an easy task to work with video, and when it comes to teaching students about video analysis an important aspect is that video analysis is not only about the development of codes but also about being able to identify concrete problems and develop trustworthy outcomes. Codes that are being developed need to be tested and 'tinkered' with so they can become building blocks that can be put together, taken apart, and recombined (Resnick, 2007). Working with video ethnography allows for the capture and potentially systematic analysis of human interactions. The challenge is, to move beyond descriptions, to not only build on the rich and insightful impressions that can be gained, but to look for patterns that are traceable and can be broken down into smaller units. The art of identifying cultural patterns through ethnographic ways is about 'making culture explicit' (Wolcott, 1999, p. 81). However, the complexity of the rich data that video recordings capture makes this a difficult task to accomplish especially for those who are new to ethnography.

The argument presented in this article was not to be 'thinking about algorithms' or 'thinking with algorithms' but rather to present an argument on what it means to apply the principles of 'algorithmic thinking' to

analyzing complexity as captured on video. Finding a concrete framework for thinking about initially unstructured data is something that students can find very difficult. Just knowing how and where to start can be overwhelming sometimes, resulting in complete intellectual paralysis. Ole Ravn Christensen (2004) writes that our ability to think analytically means that people utilise rules that can be applied across different scenarios of the same kind. However, we should not reduce this analytical ability to a mechanical calculation but add humanistic angles that shape our physical and cultural environment, since human intelligence is about more than reduction. While video ethnography opens up opportunities to explore the complex dimensions of materiality, embodiment, time, space and multimodality, utilizing an algorithmic thinking approach to the analysis of data can add causal, spatial and temporal dimension to classical ethnographic descriptions. Utilising algorithmic thinking approaches in teaching on how to approach the analysis of video can assist in the detailing and contextualising ethnographic practices.

Disclosure Statement

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REFERENCES

- Aarsand, P., & Forsberg, L. (2010). Producing children's corporeal privacy: ethnographic video recording as material-discursive practice. *Qualitative Research, 10*, 249–268. doi:10.1177/1468794109356744
- Alrø, H., & Dirckinck-Holmfeld, L. (1997). *Videoobservation*. Aalborg: Aalborg Universitetsforlag.
- Beebe, B. (2014). My journey in infant research and psychoanalysis: Microanalysis, a social microscope. *Psychoanalytic Psychology, 31*, 4–25. doi:10.1037/a0035575
- Brennan, K., & Resnick, M. (2012). New frameworks for studying and assessing the development of computational thinking. In *Proceedings of the 2012 Annual Meeting of the American Educational Research Association (AERA)*, Vancouver, pp. 1–25.

- Christensen, O. R. (2004). Tænkning som kalkule: jagten på det perfekte erkendelsesprog. J. Christensen (Ed.), *Vidensgrundlag for handlen* (pp. 103-122). Aalborg: Aalborg Universitetsforlag.
- Denning, P. J. (2010). What is computation. Ubiquity Symposium. Association for Computing Machinery. Available at http://www.kumlander.eu/itv0010/docs/101108_denning_symposium01.pdf (accessed 30 November 2016)
- Elmesky, R. (2015). Video selection and microanalysis approaches in studies of urban science education. In C. Milne, K. Tobin, & D. DeGennaro (Eds.), *Sociocultural studies and implications for science education* (pp. 95–115). Dordrecht: Springer.
- Fraser, M., Biegel, G., Best, K., Hindmarsh, J., Heath, C., Greenhalgh, C., & Reeves, S. (2005). Distributing data sessions: Supporting remote collaboration with video data. *First International Conference on e-Social Science*, 22–24 June, Manchester.
- Futschek, G. (2006). Algorithmic thinking: The key for understanding computer science. In R. T. Mittermeir (Ed.), *Informatics education – The bridge between using and understanding computers* (pp. 159–168). Heidelberg: Springer.
- Garfinkel, H. (1994). *Studies in ethnomethodology*. Cambridge: Polity Press.
- Goodwin, C. (2000). Action and embodiment within situated human interaction. *Journal of Pragmatics*, 32, 1489–1522. [https://doi.org/10.1016/S0378-2166\(99\)00096-X](https://doi.org/10.1016/S0378-2166(99)00096-X)
- Goodwin, M. H., & Goodwin, C. (2000). Emotion within situated activity. In N. Budwig, I. C. Uzgiris, & J. W. Wertsch (Eds.), *Communication: An arena of development* (pp. 33–54). Mahwah, NJ: Lawrence Erlbaum.
- Goodwin, M., Cekaite, A., & Goodwin, C. (2012). Emotion as stance. In M. L. Sorjonen & A. Peräkylä (Eds.), *Emotion in interaction* (pp. 16–41). Oxford and New York: Oxford University Press.
- Jordan, B., & Henderson, A. (1995). Interaction analysis: Foundations and practice. *The Journal of the Learning Sciences*, 4, 39–103.
- Kaptelinin, V., & Nardi, B. A. (2006). *Acting with technology: Activity theory and interaction design*. Cambridge, MA: MIT Press.
- Katz, J. (2015). A theory of qualitative methodology: The social system of analytic fieldwork. *Méthod(e)s: African Review of Social Sciences Methodology*, 1, 131–146. <https://doi.org/10.1080/23754745.2015.1017282>
- Klette, K. (2009). Challenges in strategies for complexity reduction in video studies. Experiences from the PISA+ study: A video study of teaching and learning in Norway. In T. Janik & T. Seidel (Eds.), *The power of video studies in investigating teaching and learning in the classroom* (pp. 61–82). New York: Waxmann.
- Klette, K. (2010). Blindness to change during processes of spectacular change: What do educational researchers learn from classroom studies? In A. Hargreaves, A. Libermann, M. Fullan, & D. Hopkins (Eds.), *Second international handbook of educational change* (pp. 1001–1017). Dordrecht: Springer.
- Koschmann, T., Stahl, G., & Zemel, A. (2004). The video analyst's manifesto: (or the implications of Garfinkel's policies for the development of a program of video analytic research within the learning sciences). In *Proceedings of the 6th International Conference on Learning Sciences* (pp. 278–285). Santa Monica, CA: International Society of the Learning Sciences.
- Parisi, L. (2016) Automated thinking and the limits of reason. *Cultural Studies ↔ Critical Methodologies*, 16, 471–481. doi:10.1177/1532708616655765.
- Psathas, G. (1980) Approaches to the study of the world of everyday life. *Human Studies*, 3, 3–17.

- Resnick, M. (2007). Sowing the Seeds for a More Creative Society. *Learning & Leading with Technology*, 35, 18–22.
- Robben, A. (2007). Sensorial fieldwork. In A. Robben & J. A. Sluka (Eds.), *Ethnographic Fieldwork: An Anthropological Reader* (pp. 443–449). Oxford: Blackwell.
- Roehl, T (2012). Disassembling the classroom—an ethnographic approach to the materiality of education. *Ethnography and Education*, 7, 109–126.
- Stahl, G., Koschmann, T., & Suthers, D. (2006). Computer-supported collaborative learning: An historical perspective. In R. K. Sawyer (Ed.), *Cambridge handbook of the learning sciences* (pp. 409–426). Cambridge: Cambridge University Press.
- Wing, J. M. (2008) Computational thinking and thinking about computing. *Philosophical transactions of the royal society of London A: mathematical, physical and engineering sciences*, 366, 3717–3725.
- Wolcott, H. F. (1999). *Ethnography: A way of seeing*. Oxford: Altamira Press.

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