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Video capture of human behaviors: toward a Big Data approach Louis Tay, Andrew T Jebb and Sang Eun Woo



The lowering costs of cameras and data storage have led to an increasing volume of video data from a wide variety of sources. In this review, we analyze four sources of video data (*i.e.*, traditional laboratory cameras, wearable cameras, public cameras, and private cameras), highlighting the strengths and limitations of each source regarding its utility for capturing human behaviors. While there will be technical and ethical challenges in using video camera data for human behavior research, we see promise in increased fidelity for assessing and analyzing various types of human behaviors, including behavioral occurrence, change, and development, and socio-ecological contexts. We encourage the judicious collection and secure storage of large-scale video data and the development of integrative video analytics for human behavior research.

Address

Purdue University, United States

Corresponding author: Tay, Louis (stay@purdue.edu)

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Video can be a rich source of human behavior data for social science research due to its ability to capture images from moments to months. Behavioral researchers have used video cameras to capture facial and body information, language use, and social interactions [1,2]. Video footages are often considered 'self-documenting,' as they provide the contexts needed for interpreting and understanding behaviors [3–5]. More recently, cameras that are wearable or placed in public spaces (and connected to networks) are becoming widespread, opening new channels of behavioral information and research [6]. With these as a backdrop, the current article discusses opportunities and challenges in using different sources of video data for social science research and how they can be harnessed at scale toward a Big Data approach. We focus on four major sources of video data: traditional laboratory cameras, wearable cameras, public cameras, and private cameras. These categories are not natural kinds but reflect fuzzy sets for the purposes of discussing types of video data. Figure 1 shows the overarching process in which video data from these sources may be stored, analyzed, and used in behavioral research $[7^{\bullet}, 8^{\bullet}]$. Most notably, video data can enable behavioral *detection* (*e.g.*, frequency, patterns), capture behavioral *change* and/or *development* over time (*e.g.*, episodes, interactions, life-span), and inform the *contexts* in which behaviors are enacted, facilitated, or constrained (*i.e.*, locations, countries).

Traditional laboratory cameras

Since the 1950s, standalone video cameras have been an unobtrusive and informative method of data collection in behavioral science laboratories [3]. They feature prominently in current discussions on methodological innovation [9–11] and empirical science [12–18]. Videos have been used in a variety of ways to understand different social phenomenon and communication patterns. For instance, video cameras have recorded how children exhibit the *bystander effect*, the well-replicated phenomenon in which the presence of others inhibits prosocial behaviors due to the diffusion of responsibility [18]. In another case, videos have been used to capture gender differences in stress communication (*e.g.*, stating that one feels stressed) and social support between couples [12].

As shown in Table 1, in laboratory settings, video cameras capture third-person views, and researchers have control over many video attributes, including resolution, positioning, recording, and sound capture. This enables high fidelity recording facial, body, or interactive behaviors for specific research purposes. Given the specificity in the types of research questions sought, coding of such data is frequently done manually. Despite these strengths, there are also challenges associated with these data. Data collection may be time-consuming (e.g., managing participants and recording) or expensive (due to participant payments). Further, because recordings are oriented toward specific research questions, they tend to focus on a smaller range of samples and contexts, often leading to limited generalizability of the study findings. Big Data approaches are now being developed through video repositories that enable video data reuse by other researchers. For example, Databrary is a video repository for developmental scientists funded by the National Science Foundation and the National Institutes for





Sources of video data and processes for addressing key themes in behavioral research.

Health (https://nyu.databrary.org/). Through cloud technology, researchers can quickly identify and harness multiple video streams across the globe, addressing new research questions and the possible generalizability of behaviors.

Wearable cameras

Recently, smart eyewear technology has opened possibilities for Big Data approaches through the collection of individual video data over an extended time. Much of this can be traced to the initial development of head-mounted

Table 1

Video data type	Properties	Opportunities	Challenges
Traditional Laboratory video cameras	Views: Third-person views Camera control: High control for camera resolution, positioning, recording, sound Coding: Manual human coding Participation: Voluntary/paid participation	Fine-grained behavioral capture of specific behavioral research questions Increasing data reuse through shared video repositories	Potentially costly in time and finances due to manual management of participants Potentially limited samples depending on recruitment or recording context
Wearable video cameras	Views: First-person views Camera control: Depends on whether participants provide their own camera data or if researchers provide wearable cameras Coding: Manual coding; Machine- learning algorithms to code behaviors Participation: Voluntary/paid participation	High ecological validity Connectable to other types of wearable sensors for additional information (e.g., location) Possible interaction with participants through video camera device	Low proliferation of wearable video cameras; limited samples Privacy concerns for other individuals within sphere of video capture
Public video cameras	Views: First or Third-person views Camera control: Low Control Coding: Manual coding; Machine- learning algorithms to code behaviors Participation: Public behaviors	High ecological validity Convenient for researchers to use existing video camera infrastructure	Need to find the right cameras to capture specific types of behaviors Differences in the attributes of public cameras Requires substantial data storage Difficult to automatically extract of behaviors across a wide variety of cameras and contexts Privacy concerns as individuals may be identifiable and/or locatable
Private video cameras	<i>Views</i> : First and Third-person views <i>Camera control</i> : High control <i>Coding</i> : Depends <i>Participation</i> : Voluntary participation	Capture of unique behaviors in specific settings Videos shared within social networks	Possible restrictions using private video data for research There may be restrictions from social media platforms to access videos Private video data may not be relevant for social behavioral research Privacy concerns for other individuals within sphere of video capture

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