Incidence of Electrode Bridges in Publicly Available EEG Data: An Exploratory Survey

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Introduction

In multichannel EEG montages, channels can easily be electrically bridged by electrolyte spreading between adjacent electrode sites [5,14] or equipment defects (e.g., plug or cable shorts). Although rarely acknowledged in the literature, such bridges have the potential to severely distort (i.e., spatially low-pass filter) an EEG or ERP topography, confounding conventional descriptions and inferences while invalidating source localization estimates. Surprisingly, the prevalence of bridging in data contributing to the literature is unknown.

Theoretically and practically, bridged channels can be identified by their (nearly) identical waveforms, but this labor-intensive visual search may be replaced by a more systematic numerical approach utilizing an electrical distance measure [14]. In the present study, we evaluated the incidence of bridging in a sample of publicly-available EEG datasets using an automated analysis of the frequency distributions of epoch-by-epoch electrical distances [8].

EEG Data

Public EEG datasets were defined as such if these data were freely available on the Internet for download, either directly or upon request. Datasets were used if an associated publication could be found and if EEG data were recorded with at least 20 electrodes and included at least 15 sessions. A "session" was defined as a single time period during which an electrode cap was applied and EEG data were acquired for at least 50 seconds. Five datasets meeting these selection criteria were used for this survey [1-3,6,9,10,12,13] and randomly labeled A-E (with a subscript indicating the number of channels). The data were minimally preprocessed, although sets A_{32} (50-Hz notch, 100-Hz high-pass), B_{64} (0.1 Hz high-pass, 60 Hz low-pass) and C_{22} (0.5-50 Hz band-pass, 50 Hz notch) had already been filtered. Data were acquired using a variety of reference schemes, including acquisition- or system-specific references, but all sessions were re-referenced to vertex (Cz) during preprocessing.

Table 1. Core characteristics of data included in current study.

Dataset_{Number of channels}	A_{32}	B_{64}	C_{22}	D_{32}	E_{54}
EEG channels	32	64	22	32	54
Number of subjects	16	109	9	32	5
Sessions per subject	2	1	2	1	3
Total sessions	30[a]	109	18	32	15

[a] 2 out of 32 sessions excluded.

Preprocessing

All data from a given session were resampled to 128 sps and converted to BDF format using EEGLAB [3], then merged into a single file and converted to NeuroScan 16-bit .cnt format using PolyRex [7]. All channels corresponding to recording sites that were not an integral part of an electrode cap (e.g., Nose, EOG) were removed. Bad channels were manually flagged after visual inspection and sections that showed signs of data saturation/clipping were automatically rejected [11]. The data were epoched (128 samples, not event-locked) and filtered (.01-30 Hz bandpass, 24 dB/octave, FIR [11]).

Two sessions from dataset A_{32} were excluded before analyses because of persistent recording artifacts (lack of typical EEG activity/amplitudes, more than 25% of the EEG channels flagged as bad).

Electrical Distance

Contrary to common perception, electrical bridging is not readily apparent when viewing continuous, epoched, or averaged data. However, the intrinsic Hjorth algorithm, originally implemented in NeuroScan 3.0, has been shown to be useful in detecting bridging [5,14]. This algorithm computes the electrical distance (ED) of all *pairwise* potential difference waveforms to identify bridged channels[14].

A potential difference waveform is defined as the difference between the time-varying potentials (P) of channels i and j, computed as: $P_{(i-j)}(t) = P_i(t) - P_j(t)$

The ED of that difference waveform is the temporal variance of the waveform, defined as:

$$ED_{i-j} = \frac{1}{T}\sum_{t=1}^{T}\left(P_{i-j}(t) - \overline{P_{i-j}(t)}\right)^2$$

In the current study, bridged electrodes were identified using common features in frequency distributions of electrical distances, similar to the artifact rejection method outlined by Kayser and Tenke [8].

Bridging Example

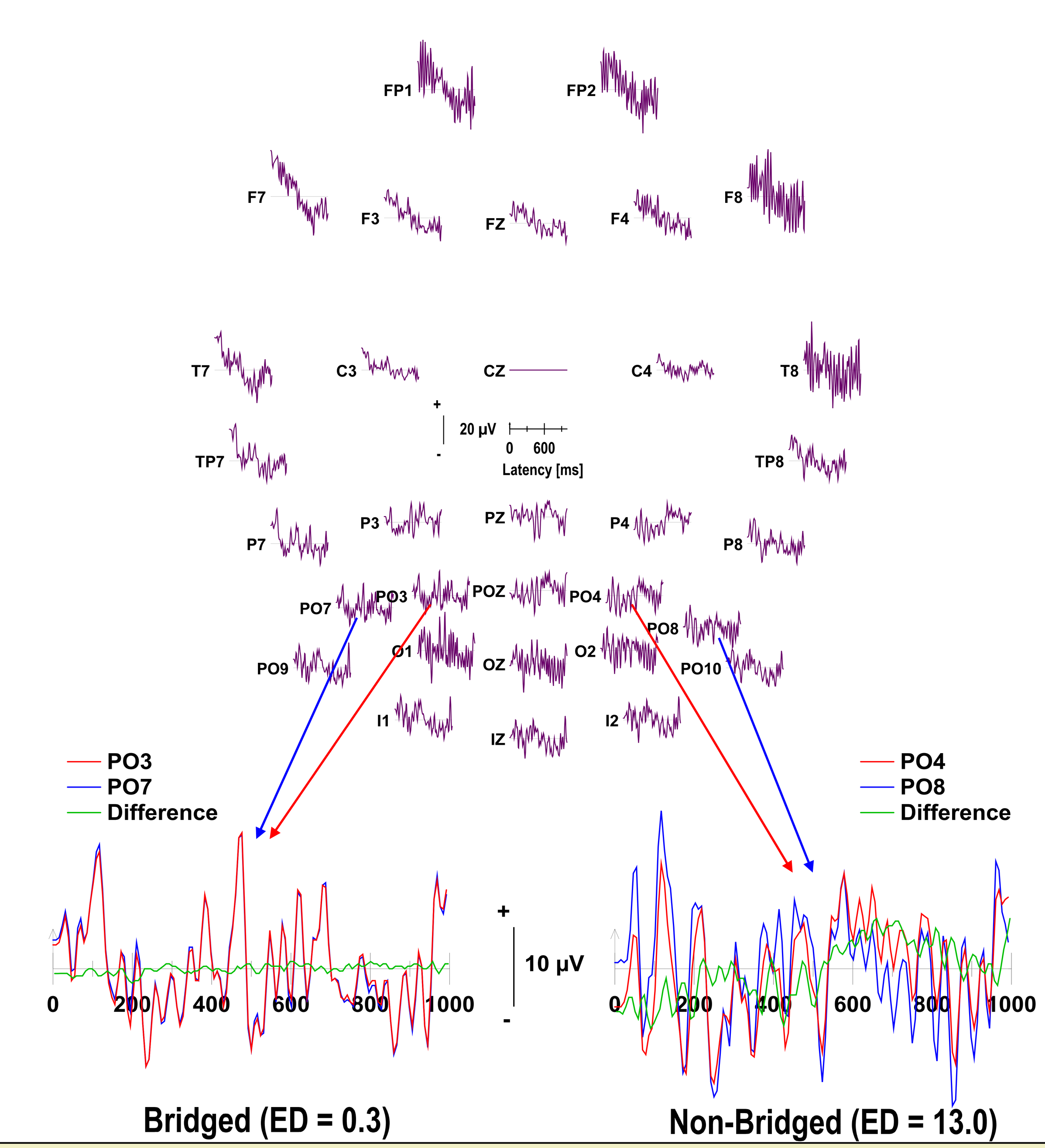

Fig. 1. A single sweep from dataset A_{32} with 6 bridged electrodes (6/32 channels). Enlarged, superimposed waveforms exemplify bridged (PO3/PO7) and non-bridged (PO4/PO8) pairs of adjacent channels. The corresponding difference waveforms (green), along with their respective EDs, quantify the degree of similarity, which can in turn be used to operationalize electrode bridging.

Detecting Electrode Bridges

Bridged electrodes were identified session-by-session. Pre-processed, epoched data were imported using EEGLAB and analyzed in Matlab using the following algorithm:

1. Data were epoched to form an *n (channels) x m (epochs)* matrix.
2. An *n x n x m* ED matrix was computed from the epoched data.
3. Electrical distances were scaled by their associated median (scale factor = 100 / median).
4. The electrical distances were summarized by their frequency distribution (bin size = 0.25). Sessions with bridged electrodes had a characteristic peak near zero (Fig. 2B). This local ED peak (LP) was identified when present.
5. If no local peak existed with an ED ≤ 5, the ED cutoff was set to 0.
6. The local minimum (LM) following the local peak with an ED ≤ 10 was automatically identified and set as the ED cutoff.
7. If 50% or more of all epochs for any given pair of channels were less than or equal to the ED cutoff, both channels were classified as bridged.

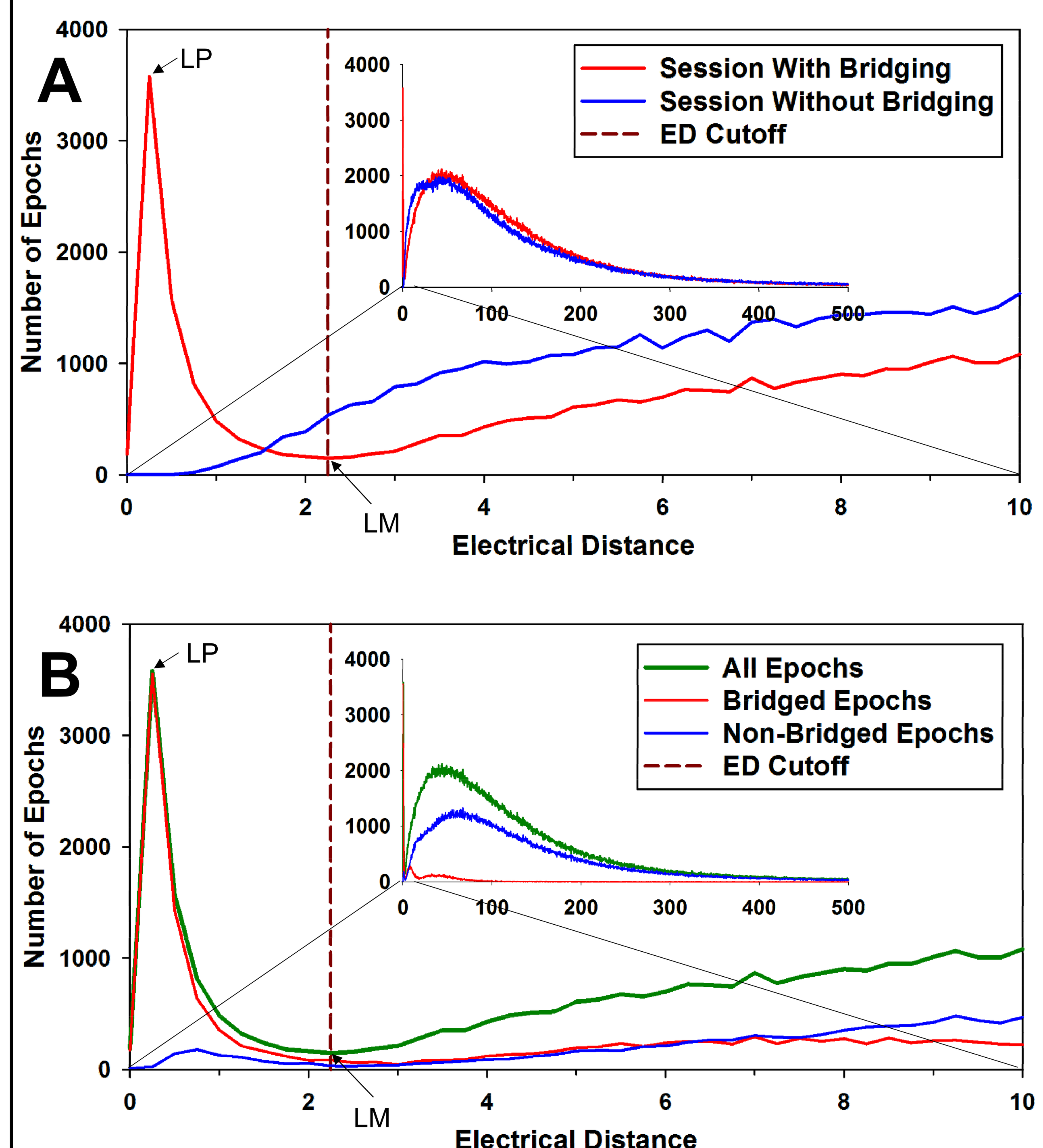

Fig. 2. Frequency distributions of electrical distances: number of epochs as a function of electrical distance (insets show complete frequency distributions of electrical distances). **A.** Partial frequency distributions of low electrical distances (range 0 to 10) from two sessions of dataset A_{32}, one with electrode bridging (session containing sweep shown in **Fig. 1**) and one without. **B.** Partial frequency distributions from session shown in **A** (red), separately plotted for epochs from bridged and non-bridged electrode pairs.

Results

Table 2. Electrode bridging by dataset.

Dataset	A_{32}	B_{64}	C_{22}	D_{32}	E_{54}
Number of sessions with bridging	26	82	0	0	2
Percentage of sessions with bridging	84	75	0	0	13
Mean percentage of bridged electrodes in EEG montage	18	10	0	0	0.5

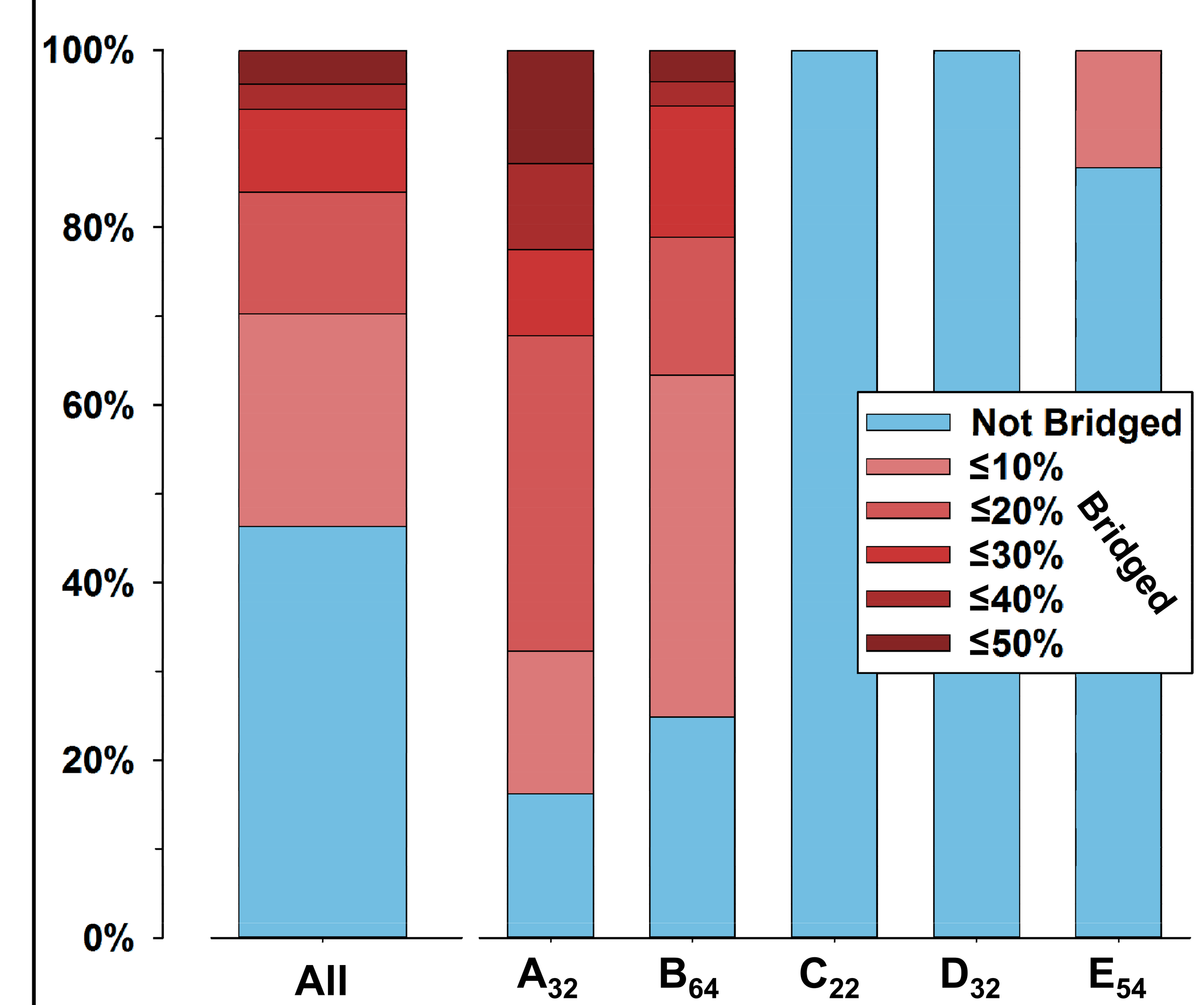

Fig. 3. Prevalence of electrode bridges across all and for each dataset. Each bar shows the percentage of bridged electrodes in the EEG montage. Bridges were detected in three of the five datasets (red bars in A_{32}, B_{64}, and E_{54}, but not C_{22} or D_{32}).

Conclusions

- **Electrode bridging occurred quite frequently (54% across all sessions) in the surveyed datasets; however, profound differences were revealed between individual datasets (Table. 2; Fig. 3).**
- **The automated algorithm outlined above is simple and compelling, allowing for easy identification of electrode bridging (Fig. 2).**
- **Given the high prevalence of electrode bridging for some datasets, EEG recordings should be routinely screened for bridges prior to analysis to avoid significant pitfalls stemming from unknown, and perhaps systematic, distortions of EEG topographies.**

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