Sebastian Kubitschko • Anne Kaun
Editors

Innovative Methods in Media and Communication Research

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Editors
Sebastian Kubitschko
University of Bremen (ZeMKI)
Bremen, Germany

Anne Kaun
Södertörn University
Huddinge, Sweden

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Foreword to 'Innovative Methods in Media and Communication Research'

How we research the social world can seem to be the concern only of professional academics. Even among academics, books about methods tend to be the books you consult only when you have to, while debates ***about*** methods (methodological debates), although they sometimes come to the fore in particular academic fields, generally do so under disguise, as disputes about 'ontology', new paradigms, and the like. A major collection of essays by young scholars on what is at stake in innovative methods is therefore a notable event.

The context indeed could not be more urgent. The transformations of what we still try to call the 'media' environment over the past quarter-century have been profound. Twenty-five years ago the challenge for media and communications scholars was to reflect on the implications of expanding television channels and everyday video recording. In the early years of the internet's commercialization, modes of internet access seemed to play out in a parallel world of their own—the world of 'cyberspace'—which attracted its explorers and methodological pioneers. Yet their work could safely be ignored by the mainstream of media research, although by 2000 it was clear that the internet was going at some point to bring major transformations.

Those times of 'normal science' and quarantined exploration seem unrecognizable today. The past fifteen years have disturbed the comfortable division of labor in media research between mainstream and innovative margins, and in their course dismantled the boundaries around media research itself. No actual or would-be researcher of 'media' today can avoid the questions of ***where exactly*** to 'cut in' to our lives with media, ***why***

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CHAPTER 7

Beyond Blobology: Using Psychophysiological Interaction Analyses to Investigate the Neural Basis of Human Communication Phenomena

Richard Huskey

Communication scholars have long investigated the relationships between communication phenomena and cognitive processes, although few have looked at the neural architecture that enables these relationships. As a consequence, many communication theories treat the brain as an unknowable black box. Rapid advances in brain-imaging technologies have allowed for the systematic investigation of the mind/brain and researchers are increasingly utilizing these methods to examine the neural basis of human communication behavior.

Early brain-imaging studies typically focused on identifying the neural substrates of a given psychological process. Today, large-scale meta-analyses now show that the same neural structures are often involved in a diverse array of cognitive processes (Yarkoni et al. 2011). If the same brain regions are involved in a variety of cognitive process, then brain-mapping studies alone can tell us only so much about the neural organization of the mind. Accordingly, researchers are increasingly investigating how connected

R. Huskey (✉)
Ohio State University, Columbus, OH, USA
e-mail: huskey.29@osu.edu

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neural structures interact with one another in order to enable various cognitive processes (for example, Bassett and Gazzaniga 2011; Friston 2011; Weber et al. 2015a).

This chapter introduces communication scholars interested in conducting functional magnetic resonance imaging (fMRI) investigations to psychophysiological interaction analysis (PPI; Friston et al. 1997), a method for assessing task-modulated brain–network connectivity. Given that fMRI is still relatively uncommon among communication researchers, this chapter begins with a brief introduction to how the technology works and what sort of questions can be addressed with this method. With that said, readers are encouraged to consult more detailed introductions (see Weber et al. 2015b) or one of the many excellent textbooks on the topic (for example, Huettel et al. 2009). From there, this chapter provides a brief overview of the rationale for understanding the mind (and the communication phenomena it enables) as resulting from dynamic interactions between various brain structures. This includes a specific example where a higher-order cognitive process, flow experiences (Csíkszentmihályi 1990) resulting from media use, is thought to emerge as the result of a neural coupling between attentional and reward networks (Weber et al. 2009). This chapter then discusses the methodological particulars associated with using a PPI analysis to test the synchronization theory of flow, before concluding with a broader outlook on applications to communication theory and research. Specifically, it will discuss how investigations of neural connectivity can be used for theoretical falsification, conceptual refinement, and distinguishing constructs that have similar phenomenological characteristics and behavioral outcomes.

How Does fMRI Work and What Sort of Questions Can It Address?

In the most general sense, fMRI is a method for identifying the brain regions that are recruited during a given psychological process. This inference is well established and corresponds to the following logic: (1) a specific task or stimulus (2) results in localized neural activity that (3) includes changes in metabolic demands for oxygen and glucose, thereby (4) necessitating an increase in localized blood flow that (5) alters the ratio between oxygenated and deoxygenated hemoglobin (known as the blood oxygen level–dependent, or BOLD, contrast), where (6) this change is detectable by magnetic resonance techniques (DeYoe et al. 1994). Importantly, this signal is best understood as a measure of neuronal input and ***not*** as a measure of neuronal output (Logothetis et al. 2001; Logothetis and Pfeuffer 2004). This means that fMRI captures an indirect measure of neuronal activity, one that is characterized by a poor signal-to-noise ratio (Huettel et al. 2009).

Weber and colleagues (2015b) identify three general classes of questions that fMRI can be used to address. The first deals with localization and is focused on identifying the structures that are recruited during different communication processes. The second and third questions ask whether specific neural structures are recruited for distinct communication processes, or if activity in these structures is observable during a variety of processes. The takeaway is that fMRI is useful for addressing a narrowly constrained set of questions. This may be one of the reasons why the technique has seen limited adoption within the communication discipline. However, recent inquiries have demonstrated the utility of using fMRI for communication theory building and testing, particularly in instances where previous efforts have been stymied by the limitations inherent in more traditional measures (see Weber et al. 2015a). The remainder of this chapter details (1) a rationale for a networked theory of the mind; (2) a method for examining neural connectivity; and (3) the ways in which this can be used to advance communication theory and research.

What Is Connectivity and Why Does It Matter?

Early theorizing understood the brain as an information processing system where modular neural structures were recruited to perform unique cognitive tasks (Fodor 1983). Accordingly, the first fMRI studies set out to localize cognitive functions to specific brain regions. These brain-mapping studies provided a foundational understanding of the mind's neural organization and paved the way for modern conceptualizations of the mind/brain. Today, a growing body of research demonstrates that the brain is a complex system that (1) recruits multiple structures to perform different computational tasks; where (2) these structures work together or one exerts an influence over another in order to perform computations; and (3) the output of this computation can be characterized as greater than the sum of the individual subcomponents (Bassett and Gazzaniga 2011). This is known as emergence (Weber et al. 2015a), a phenomenon where complex higher-order cognitive functions emerge from dynamic interactions between distributed networks of neural modules (Strogatz 2003). Indeed, mounting evidence supports the view that different cognitive processes result from unique interactions between neural networks (Bullmore and Sporns 2012; Davison et al. 2015; Gu et al. 2015; Hermundstad et al. 2013, 2014; Petersen and Sporns 2015).

The relevance of neural connectivity and its application to communication research might not be immediately clear to scholars unaccustomed to thinking about psychological processes in such terms. To help overcome this lack of familiarity, let us consider a cognitive process commonly cited in the communication literature from a connectivity perspective: flow theory (Csíkszentmihályi 1990). Flow is a positively valenced subjective experience characterized by feelings of complete attentional focus, a loss of temporal awareness, diminished self-consciousness, and the sense that an activity is inherently rewarding. Weber et al. (2009) draw on the latest developments in the cognitive neuroscience literature in order to link the subjective experience of flow with well-established neuropsychological processes. Their synchronization theory of flow can be broken down into four premises. First, neural networks are capable of oscillating at the same frequency, and this shared oscillation (synchronization) indicates that networks are working together. Second, synchronization is a discrete state. Networks are either in sync or they are not. Third, the synchronization of neural networks is energetically cheap and the combined effect of synchronized networks is greater than the sum of the individual parts. The final assumption understands flow as the result of a synchronization between attentional and reward networks under conditions of a balance between task challenge and individual skill. Together, these assumptions are thought to account for the wholly absorptive and highly rewarding nature of flow experiences. The next sections discuss the practical aspects of using PPI analyses to test synchronization theory's connectivity prediction.

Neural Connectivity

Connectivity can be broken down into three subcategories: structural connectivity, functional connectivity, and effective connectivity (Friston 2011). Structural connectivity is concerned with the white-matter fiber tracts that connect different brain structures, and it is structural connectivity that enables different brain regions to work together. Cognitive processes modulate the strength of neuronal connections between brain

regions. This basic observation underlies the principles of functional and effective connectivity, between which Friston (2011) is careful to distinguish. Functional connectivity describes statistical dependencies (for example, correlation) between neural activity in two or more brain regions. By comparison, effective connectivity is concerned with the influence that one structure exhibits over another.

Importantly, methods that were once useful for testing functional connectivity have since been modified to test effective connectivity. As an example, modern coherence analysis (which examines the correlation between two neural regions in the frequency domain) can be modified to assess time-shifted correlations between brain regions (Ashby 2011). In such analyses, one region is thought to exert influence on another when neural activity that has been shifted back in time correlates with temporally unaltered activity in another region. Here, a coherence analysis begins to look more like an assessment of effective connectivity. This may be one of the reasons why functional connectivity is often used as an umbrella term to describe analyses that investigate statistical relationships (including directionality and influence) between structurally connected brain regions (O'Reilly et al. 2012). For simplicity's sake, this chapter uses the term functional connectivity when referring to methods for assessing both functional and effective connectivity.

A key idea of structural connectivity is that it constrains functional connectivity, in that neural structures cannot be functionally connected if they are not also structurally connected (Friston 2011). Accordingly, structural connectivity at least partially explains individual differences in task-related neural activity (Miller et al. 2012) and even partially predicts individual differences in functional connectivity (Chu et al. 2015). However, after a critical developmental period (and barring any neurological damage), structural connectivity within an individual remains largely invariant (Seung 2012). Therefore, if we wish to understand how communication phenomena modulate brain states, then we are primarily interested in understanding how functional connectivity differs between communication processes. This chapter necessarily narrows its focus to statistical methods for assessing functional connectivity, while recognizing that it is structural connectivity that enables functional relationships in the first place.

In practice, researchers interested in assessing functional connectivity have a vast number of analytic methods at their disposal. Wang et al. (2014) identify forty-two different approaches belonging to seven different families of analysis (that is, correlation, h^2, mutual information, coherence, Granger causality, *AH*, and transfer entropy), and even more analyses are available (see, for example, Ashby 2011; Friston 2011). While each has utility for testing communication research questions, it is beyond the scope of this chapter to address all these methods. Instead, the chapter provides an introduction to PPI analysis, a common approach for assessing functional connectivity that builds on statistical principles with which communication scholars are already quite familiar.

Psychophysiological Interactions

The primary utility of PPI analysis is an investigation into task-modulated functional connectivity. The analysis itself is based on two fundamental principles of neural activity (Friston et al. 1997). First, neural activity in two or more regions is correlated when these regions are working together. The second principle is that a task should modulate the strength of the correlation between two regions of interest (ROIs). It is this second idea that is central to PPI analysis. One benefit of PPI is that the underlying mathematical principles are relatively easy to understand for researchers who are already familiar with standard statistics and fMRI analyses based on the general linear model (GLM). There are three steps for conducting a basic PPI analysis: select a seed ROI, extract the neural time series data for that ROI, and define a GLM (O'Reilly et al. 2012).

ROI Selection

PPI analyses are highly hypothesis driven (Friston et al. 1997). The first step in any PPI analysis is to identify a seed ROI that is thought to exert task-dependent influence over target ROIs (O'Reilly et al. 2012). There are three strategies for seed selection. The first selects a seed ROI based on anatomical or theoretical models. Large-scale meta-analyses of connectivity data may be particularly useful here (see, for example, the online platform http://neurosynth.org and Richardet et al. 2015). A second approach selects a seed ROI based on a previous GLM analysis; this is known as a functionally defined ROI (fROI).[1] A final approach selects a seed ROI based on exploratory analysis, such as an independent component analysis (ICA).

Time Series Extraction

Once a seed ROI has been defined, the neural time series data must be extracted (for each subject) from that region (O'Reilly et al. 2012). This procedure can be completed using freely available brain-imaging analysis software such as the Wellcome Trust Centre for Neuroimaging Statistical Parametric Mapping software package (SPM; http://www.fil.ion.ucl.ac.uk/spm) or the Oxford Center for Functional MRI of the Brain (FMRIB) Software Library (FSL; http://www.fmrib.ox.ac.uk/fsl). Importantly, this extracted time series has already been convolved with a hemodynamic response function (HRF), which has implications for subsequent data analysis. Functional connections in the brain occur at the neuronal level and not at the multi-determined BOLD signal level (Friston et al. 1997). Therefore, any model that uses unmodified time series data extracted from a seed ROI is necessarily misspecified (Gitelman et al. 2003). One approach for dealing with this issue is to perform a deconvolution procedure[2] on the extracted time series data. While this might sound like the opposite of a convolution procedure, the multi-determined and regionally varying nature of the BOLD signal complicates the calculations, especially for resting-state fMRI data where the timing of neural events is unknown.

Unfortunately, there is no perfect way to deconvolve an unknown HRF (O'Reilly et al. 2012), and even the best deconvolution algorithms (for example, Bush and Cisler 2013) can introduce error. Accordingly, perceptions about the necessity of deconvolution often vary depending on experimental procedure and research lab. In practice, deconvolution is likely to matter most in fast event-related designs where events change rapidly in comparison to the relatively slow hemodynamic response (Gitelman et al. 2003). Block designs, by comparison, should result in a saturation of localized blood flow in response to task-related neural activity. Therefore, it is less likely that deconvolution is as crucial for experiments that employ a block design (O'Reilly et al. 2012).

Defining a GLM

The final step in a basic PPI analysis is to define a general linear model (O'Reilly et al. 2012). The simplest GLM includes three regressors (or explanatory variables, EVs): a psychological EV, a physiological EV, and an interaction term. The psychological EV (PSY) is the task sequence convolved with an HRF. The physiological EV (PHYS) is an $n \times 1$ matrix representing the extracted time series data for the seed ROI, where n is equal to the number of images captured during a scanning session. The final EV is an interaction term—the product of the psychological and physiological EVs. The model can be written out as follows:

$$B = \beta_1 PSY + \beta_2 PHYS + \beta_3 (PHY \times PHYS) + \beta_0 + \varepsilon.$$

Deconvolution decisions also have an impact on model specification. If the time series data were deconvolved, then the physiological EV should be reconvolved with an HRF (O'Reilly et al. 2012). If deconvolution was not applied to the time series, then convolution should not be applied to the physiological EV. It is also critical to model the main effects for both the psychological and physiological EVs, as the interaction term is likely confounded by the main effects (Cohen et al. 2003). The model should also include other confounded EVs that describe the data (for example, a linear drift term, motion artifacts), as this will make the model more accurate and therefore more sensitive (O'Reilly et al. 2012). This model is then applied to all subjects in a series of first-level analyses. Once all the first-level analyses have been completed, they can be combined in a higher-level analysis using standard procedures (see Weber et al. 2015b).

Other Considerations

One limitation inherent to PPI analyses is that the analysis is often lacking in statistical power (O'Reilly et al. 2012). This limits the potential for type I error, but is problematic in that a PPI analysis may be less sensitive for detecting functional connectivity. One reason for this is that, in the simple model defined earlier, the PSY and PHYS regressors may be correlated, thus making it difficult to detect the interaction due to the presence of main effects (Friston et al. 1997). The interaction term of interest can only account for variance above and beyond that which is explained by the main effects (Cohen et al. 2003). One possible solution is to design a study that utilizes a block design, as this approach has been shown to provide increased power compared to event-related designs (Chee et al. 2003; Cisler et al. 2014).

One final approach for increasing statistical power and reducing error is known as generalized PPI (gPPI; McLaren et al. 2012).[3] The main difference from a standard PPI (sPPI; the simplified procedure with just three

EVs already described) is that a gPPI models an EV for each factor in the experimental design, instead of modeling one EV that encodes all experimental factors. An interaction term is then modeled for each factor. By increasing the number of parameters in the model, the gPPI essentially allows for the decomposition of the interaction term and a more direct comparison of functional connectivity between task conditions. In simulation and real-world data, McLaren et al. (2012) demonstrate that the gPPI improves model fit and potentially reduces both type I and type II error. When compared to sPPI analyses, gPPI analyses are particularly more powerful for event-related designs, although they are comparably powerful for block designs (Cisler et al. 2014). Unfortunately, one complication of gPPI is that the higher number of terms increases the difficulty of beta-weight interpretation (McLaren et al. 2012).

The previous paragraph suggests that PPI analyses might be subject to type I error. O'Reilly et al. (2012) demonstrate how failing to include all sources of task-related variance in the model can contribute to spurious results. As an example, they describe a hypothetical experiment where subjects navigate a maze while undergoing fMRI scanning. In such an experiment, subjects might stop to strategize the next move, turn a corner, navigate a straight path, or finish the maze. In an analysis where each maze run, start to finish, was modeled in a block design, certain events, such as turning a corner or finishing the maze, might trigger a spike in neural activity, which boosts the BOLD signal, but not in the sustained manner that the block design assumes. Increasing model specificity (for example, a gPPI) might be one method for mitigating this concern, but this example also suggests that researchers should carefully consider whether a block design is an adequate fit for their assumptions about neural activity. Like any fMRI study, subject ability, attention, learning, and exhaustion might influence neural activity.

Finally, PPI analyses are typically based on a linear application of the GLM. However, it is well known that many neural processes are non-linear (Friston et al. 2000), and the presence of a non-linear relationship between seed and target ROIs might drive spurious PPI results (O'Reilly et al. 2012). There are possible solutions for dealing with non-linear relationships in a PPI analysis (for an extended discussion, see Harrison and Friston 2004). In one example, Weber et al. (2014a) add a quadratic term to account for non-linearities in the data. Their PPI model is as follows:

$$B = \beta_1 PSY + \beta_2 PHYS + \left(\beta_3 PSY + \beta_4 PSY^2\right) \times PHYS + \beta_0 + \varepsilon.$$

One benefit of this approach is that it enables the investigation of network criticality, or the threshold values that result in synchronization within a network (for an extended discussion of network dynamics and criticality with a particular focus on their relationship to communication phenomena, see Sherry 2015).

PPI Utility

PPI analyses have a number of benefits that make them well suited for testing synchronization theory. First, unlike exploratory methods such as ICA, PPIs are highly hypothesis driven. Synchronization theory offers explicit hypotheses concerning which alerting, orientating, and reward structures are likely involved in flow (see Weber et al. 2009), and many of these predictions see preliminary support among early brain-mapping investigations of flow (Huskey et al. 2014; Klasen et al. 2012; Ulrich et al. 2014). Together, these studies provide a strong foundation for selecting relevant seed ROIs that allow for direct tests of the theory's main hypotheses.

PPIs are also useful for extending our understanding of how synchronization theory works. In their 2009 paper, Weber and colleagues theorize that flow is the emergent property of a synchronization between attentional and reward networks. However, they do not specify the direction of influence between these structures. Recent neuroscientific results indicate that the reward value of a stimulus predicts activation in structures associated with alerting attention (for example, Stanisor et al. 2013). This suggests that neural activity in reward networks might exert influence over attentional networks during flow. PPI analyses would be useful for investigating this as yet untested hypothesis. My collaborators and I are actively conducting work in this area and our initial results are proving promising. Finally, a PPI analysis paves the way for more sophisticated techniques such as those that use graph theoretical approaches for understanding whole-brain connectivity patterns between cognitive states (see Gu et al. 2015).

Concluding Remarks and Future Directions

Communication scholars are increasingly adopting brain-imaging research methods. This chapter continues in that trajectory by explaining how PPI analyses can be used to assess communication questions with fMRI data. While PPI analyses are particularly useful for testing synchronization theory, they may also be useful for investigating other communication

phenomena. Specifically, they can be used for theoretical falsification, conceptual refinement, and as a means for distinguishing constructs that share similar phenomenological and behavioral outcomes. This chapter's discussion of the synchronization theory of flow (Weber et al. 2009) has demonstrated the utility of PPIs for theoretical falsification. However, what of the other two issues that connectivity analysis might address?

There are several opportunities for brain-imaging research to advance communication theory, but the growing body of research focused on the neural basis of persuasion provides a particularly salient example (for example, Chua et al. 2011; Falk et al. 2009, 2012; Ramsay et al. 2013; Seelig et al. 2014; Weber et al. 2014b). Many persuasion theories argue that attitude and behavior change results from an interaction between features of a message and audience characteristics. However, in a recent review, Vezich et al. (2016) argue that brain-imaging investigations of persuasion heavily implicate the role of socio-emotional processes in persuasive outcomes. As of now, these processes are not accounted for in many of the most prominent persuasion theories. This is an instance where brain-imaging analyses, particularly with a connectivity focus, can assist in refining existing theoretical models.

Neural connectivity analyses are also useful when traditional approaches (for example, self-report, behavioral paradigms) struggle to distinguish between different theoretical constructs. Returning again to flow during media use, the experience is characterized by a loss of temporal and self-awareness, intense concentration, and a pleasurable experience. Some researchers have argued that this might be related to losses in self-regulation associated with video game addiction (Wood and Griffiths 2007; Gentile 2009). A forthcoming review demonstrated that not only do flow and video game addiction share similar self-report and behavioral outcomes, but each construct is also associated with neural activation in similar brain regions (Weber et al. 2017). Nevertheless, if flow experiences during media use are different from video game addiction, then it should be possible to observe different neural connectivity patterns for each cognitive process. A recent review hypothesizes that video game addiction should be associated with a brain state where reward networks exert bottom-up control over attentional structures, while flow should be associated with synchronized connectivity between these networks (Craighead et al. 2015). This provides an example where connectivity analyses can be used to identify a biomarker for psychological processes that are difficult to assess using more traditional approaches.

More generally, the neural basis of many communication phenomena remains largely unexplored (for an extended discussion with examples for how to get started, see Weber et al. 2015a). While brain-mapping studies represent an important first step (Weber et al. 2015b), this chapter argues that connectivity analyses add crucial information about how neural structures, acting in a networked architecture, enable higher-order communication processes. Neuroscientific advances within the discipline will develop more rapidly if our early studies investigate not only brain mapping, but neural connectivity.

This is an exciting time for connectivity research characterized by considerable technical and analytic advances. At the same time, stronger magnetic fields in fMRI scanners are allowing for better structural connectivity imaging and, therefore, more biologically plausible specification of functional connectivity models (Lohmann et al. 2012). These are complemented by attempts to map the entire human connectome (Seung 2012). Recent developments such as multi-voxel pattern analysis (Norman et al. 2006) and hyper-graph techniques (Davison et al. 2015) move beyond assessing relationships between a few ROIs and allow for the analysis of complex, whole-brain network states that characterize cognitive tasks. In addition, there are serious attempts to combine both structural and functional connectivity data in large-scale databases, with the goal of developing a better understanding of human cognition and behavior (for example in the case of the Human Connectome Project). Communication scholars are familiar with thinking in network terms and have advanced many sophisticated models for assessing network architectures (Lazer et al. 2009). It is exciting to imagine a future where the skills of communication scholars will bolster investigation into the human brain.

Notes

1. Importantly, fROIs should be defined independently of the task under investigation in order to prevent artificially inflated results (see Weber et al. 2015b).
2. There are several deconvolution algorithms that can be implemented in both SPM and AFNI (National Institute of Mental Health; https://afni.nimh.nih.gov/afni, accessed on 10 August 2016). By comparison, FSL does not have a built-in deconvolution algorithm.
3. An SPM toolbox for conducting gPPI analyses is available here: http://www.nitrc.org/projects/gppi. FSL is also capable of conducting gPPI analyses.

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CHAPTER 8

As We Should Think? Lifelogging as a Re-emerging Method

Alberto Frigo

'As We May Think' is the title of an article written by Vannevar Bush (1945) at the end of World War II. His article is at the center of my discussion and provocation. While lifelogging, or rather the technology enabling ordinary individuals to capture, store, and retrieve their lives, has been much criticized by both scholars and public opinion for its privacy implications, I will make use of my chapter to provide an alternative way to look at this phenomenon, and to go as far as to propose it as an indispensable method for scholars to better sense and understand the complex media-generated landscape around them. I will do so by providing a broader historical contextualization of lifelogging and deepen the contemporary discussion on an everyday life increasingly governed by sensors and algorithms. Secondly, while inviting media scholars to embrace technical complexity in an autoethnographic fashion, I will introduce a set of instructions on how to get started on lifelogging as a research method. Lastly, I will present my own manual lifelogging methodology as a concrete example of information retrieval and subsequent knowledge production.

A. Frigo (✉)
Södertörn University, Stockholm, Sweden
e-mail: alberto.frigo@sh.se

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