Biosignal-based Spoken Communication: A Survey

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***Abstract*—Speech is a complex process involving a wide range of biosignals, including but not limited to acoustics. These biosignals - stemming from the articulators, the articulator muscle activities, the neural pathways, and the brain itself - can be used to circumvent limitations of conventional speech processing in particular, and to gain insights into the process of speech production in general. Research on biosignal-based speech processing is a wide and very active field at the intersection of various disciplines, ranging from engineering, computer science, electronics and machine learning to medicine, neuroscience, physiology, and psychology. Consequently, a variety of methods and approaches have been used to investigate the common goal of creating biosignal-based speech processing devices for communication applications in everyday situations and for speech rehabilitation, as well as gaining a deeper understanding of spoken communication. This article gives an overview of the various modalities, research approaches, and objectives for Biosignal-based Spoken Communication.**

***Index Terms*—biosignals, spoken communication, multimodal technologies, speech recognition and synthesis, speech rehabilitation, electromyography, ultrasound, functional near-infrared spectroscopy, electroencephalography, electrocorticography**

I. Introduction

Human speech production is a complex motor process, that starts in the brain and ends with respiratory, laryngeal, and articulatory gestures for creating acoustic signals of verbal communication. Physiological measurements using specialized sensors and methods can be made at each level of speech processing, including the central and peripheral nervous systems, muscular action potentials, speech kinematics (tongue, lips, jaw, etc), and sound pressure. Together, these physiological measurements are known as speech-related "biosignals" and have been used for decades to better understand the underlying mechanisms of human speech production. Modeling the mapping between physiological parameters and acoustic consequences of speech still remains a very active research field. Propelled by technological advances, an increasing number of studies have investigated speech-related biosignals in applied research focused on developing spoken communication (SC) systems. This field is referred to as "Biosignal-based Spoken Communication," and encompasses two primary tracks for converting: (1) biosignals into text (biosignal-based speech recognition), and (2) biosignals into a synthetic voice (biosignal-based speech synthesis). Examples of these two technical tracks include Brain-Computer Interfaces (BCI) for restoring communication by directly decoding cortical brain activity [1], [2], [3] into speech representations, and Silent-Speech Interfaces (SSI) [4], which offer a way to communicate privately without disturbing bystanders and / or provide voice communication for people with severe speech impairments (e.g., laryngectomy patients). Furthermore, several studies have recently investigated biosignals as a means to provide valuable articulatory biofeedback to speakers about their own voice production for increasing articulatory awareness in speech therapy or language learning (e.g., [5], [6], [7]).

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The field of Biosignal-based Spoken Communication has rapidly advanced in recent years and the IEEE Special Issue on this subject is intended as a snapshot and comprehensive review of the current state-of-the-art. This survey paper provides an overview and definition of the methods, sensor technologies, signal processing algorithms, and applications used across the field. We provide specific focus on the processing, analysis, classification, recognition, and interpretation of a large variety of biosignals representing speech and language, including a discussion on advanced machine learning approaches, as well as theory and applications related to spoken language processing. With its broad scope, this survey intends to bridge the gap between the disciplines, provide a linking structure within the special issue, and to generally provide an entry point for readers interested in this very active field of research and development.

The remainder of this survey paper is organized in five sections. Following this introduction, Section II provides a definition of "biosignals", as well as the different modes of speaking. Section III describes methods used to acquire speech-related biosignals, ranging from respiratory, laryngeal, and articulatory kinematics, to muscular and neurological activity. Section IV summarizes processing methods needed to analyze each speech-related biosignal and includes descriptions of relevant features, dimensionality reduction and compression methods. This section also discusses the usage of biosignal-based automatic speech recognition and speech synthesis. The paper ends with a discussion of the wide variety of use cases and existing applications in Section V, and a view toward the future of Biosignal-based Communication in Section VI.

II. General Definitions and Uses of Biosignals

In this section we provide a definition for *biosignals* along with a description of the most important biosignals in speech. We also define a variety of *speaking modes* referred to throughout the article.

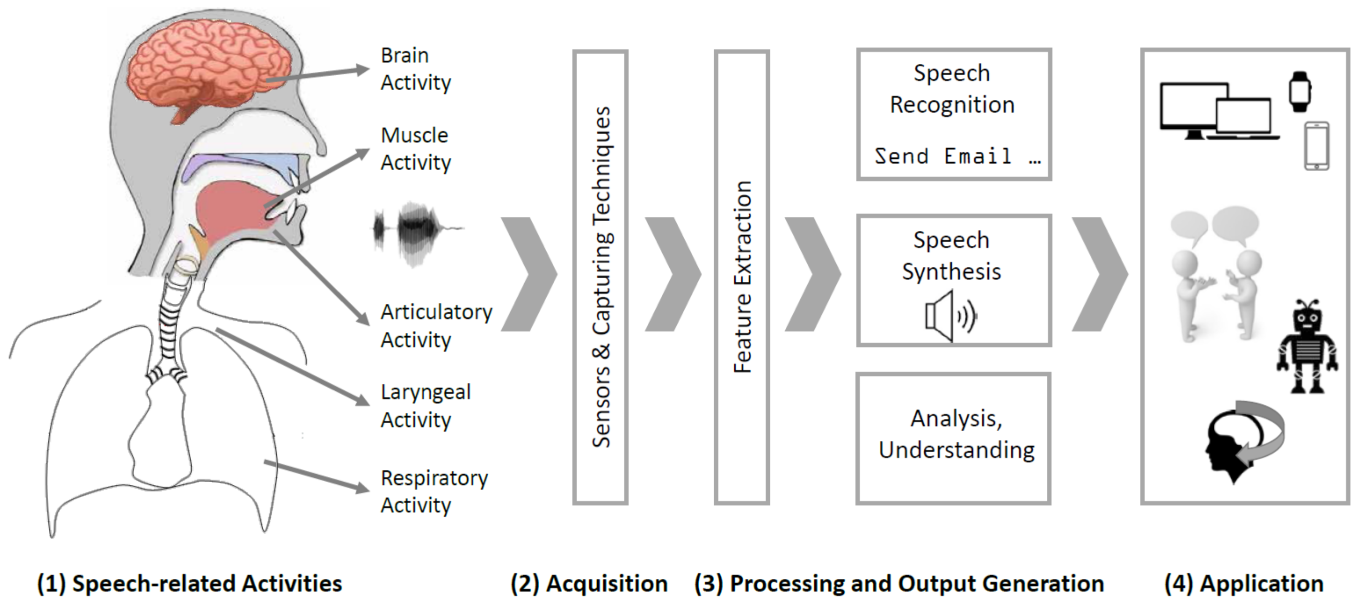

Fig. 1. Biosignal-based Spoken Communication resulting from (1) Speech-related Activities of the Human Body, (2) Signal Acquisition using various activity-dependent Sensor Technologies, (3) Biosignal processing including Feature Extraction followed by Output Generation for (4) various target Applications.

A. Biosignals

We define *Biosignals* as autonomous signals produced by human activities measured in physical quantities using different sensor technologies. Autonomous signals result from chemical, physical, and biological processes of the human organism and serve the functions of control, regulation, and information transmission throughout the body. Sensor technologies can be used to measure each signal, in terms of kinetic (force, torque, movement), kinematic (position, velocity, acceleration), optical (radiance, luminance), chemical (concentration, pH, olfactory), electrical (potential, current, resistance), acoustic (sound pressure and intensity, impedance), and thermal (temperature) quantities, resulting in the corresponding categories of biosignals.

Biosignals have been used in medical diagnostics [8] for decades. More recently, rapid advances in sensor technologies in accuracy, resolution, miniaturization, integration, connectivity, mobility, usability, costs, availability, and many other features, have propelled the application of biosignals to other contexts, including information technologies. In particular, the human-computer interaction (HCI) community has embraced biosignals to extend the number of modalities available for developing robust and intuitive devices. Information obtained from the biosignals is used to interpret not only physical states, but also affective and cognitive states, and activities of a user. Thereby, biosignals provide an *inside* perspective on human mental processes, intentions, and needs that complement traditional means of observing human interaction from the *outside*, and thus enable personalized and adaptive services [9].

In speech and language, biosignals are used for basic and translational research and development, including: voice-driven HCI, human-human interaction and communication, speech therapy, and language learning. At a basic level, biosignals can provide a comprehensive description of speech processing by reflecting all speech-related activities of the human body as depicted Figure 1 (step #1), found in the brain, the peripheral nervous system, the muscles, the speech anatomy of articulation (jaw, lips, tongue, and other orofacial structures), phonation (vocal folds), and respiration. The biosignals of speech then result from being captured through a wide variety of sensors and capturing techniques (step #2 in Figure 1, see Section III).

The remainder of this article focuses on biosignals beyond traditional acoustic waveforms captured by techniques such as electromyography (EMG), electroencephalography (EEG), electrocorticography (ECoG), intracranial microelectrodes, functional near-infrared spectroscopy (fNIRS), ultrasound (US), and permanent magnet articulography (PMA). While acoustic biosignals can only be captured during vocalizations that displace particles of the surrounding medium (usually air) by a vibrating object (usually the vocal folds), kinematic, kinetic, electrical, and optical biosignals do not rely on such air particle displacement and thus extend to many *speaking modes* beyond the audible one.

B. Speaking Modes

Speech results from modulation of the expiratory air flow from the lungs through the glottis, which is filtered by the vocal tract [10]. The acoustic transfer function of the vocal tract depends on the geometry of both oral and nasal cavities, which are configured by positions of the tongue, lips, jaw, and velum. For the purpose of Biosignal-based Spoken Communication, we distinguish different speaking *modes* based on glottal activity and intensity in Tables I & II.

Each speaking mode in Tables I & II produces sound pressure waves that can be captured by traditional acoustic-based sensors resulting in acoustic biosignals. This survey focuses specifically on biosignal acquisition from *speech produced*

TABLE I
SPEAKING MODE DEPENDENT ON GLOTTAL ACTIVITY

Modal speech	The vocal folds vibrate for voiced sounds or do not vibrate for unvoiced sounds.
Whispered speech	Turbulent flow through a constant aperture formed between the vocal folds results in only unvoiced sound.

TABLE II
SPEAKING MODE ACCORDING TO LEVEL OF EFFORT.

Normal modal speech	Modal speech at normal intensity: the "standard" mode of speaking.
Shouted speech	Modal speech characterized by higher intensity, higher pitch, and more open articulation than speech at normal intensity. It shares common properties with Lombard speech produced in noisy environments [11].
Murmured speech	Characterized by very low-intensity (voiced/unvoiced) sounds that are barely perceptible to bystanders. Residual acoustic activity can, however, be recorded using a specific microphone (see Section III-B).

without making any sound. The current literature refers to "speech-without-sound" rather inconsistently, and sometimes equivalently as, imagined, silent, covert, or inner speech, despite differences in their behavioral components. In the context of spoken communication studies, the confusion and inconsistency of terminology might be a result of different instructions given to subjects - or the lack of instructions. In Table III we propose the classification of speech-without-sounds into three levels: silent, imagined, and inner speech.

TABLE III
CLASSIFICATION OF SPEECH MODES WITHOUT ACOUSTIC OUTPUT.

Silent speech	Speakers are instructed to move their articulators as if producing normal modal speech, but to suppress their pulmonary airstream so that no sound is emitted. Silent speech production can be measured by monitoring articulatory movements using motion-capture devices, imaging techniques, or by measuring the activity of muscles (see Section III).
Imagined speech	Similar to silent speech, except movements of the articulators are also suppressed. Imagined speech in this context is identical to first-person motor imagery of speaking in which the speakers should feel as though they are producing speech rather than simply talking to themselves. Since imagined speech is produced without any articulatory movements, this speaking mode requires observations at the neural level.
Inner speech	Though there is a range of descriptions for inner speech (e.g., self-talk, verbal thinking, inner voice, inner dialogue) [12], we adopt Vygotsky's model [13] that defines inner speech as an internalized process in which one thinks in pure meanings. In contrast to imagined and silent speech, no phonological properties and turn-taking qualities of an external dialogue are retained. Thus, inner speech is even more difficult to investigate, even at the neural level of observation.

Each speaking mode in Table III has distinct challenges and opportunities for signal acquisition and application to spoken communication. Some opportunities include: (1) robustness to adverse environments, e.g., measuring articulation is less prone to acoustic noise than airborne signals; (2) less disturbing or more secure, e.g., whispered or silent speech is favored over normal modal speech in quiet environments, and silent or imagined speech allows one to communicate confidentially; and (3) rehabilitation / restoration applications for individuals with voice problems or speech disabilities, e.g., silent speech interfaces as a voice prosthesis for individuals with laryngectomy, and possibly as a neural prosthesis for speech using imagined speech (i.e., speech brain-computer interfaces) for individuals with paralysis and mutism due to neurological disease or trauma (e.g., locked-in syndrome).

In addition to challenges of recording and processing biosignals for speech without sound (section IV-D), a major challenge is precisely due to the lack of auditory feedback and, for imagined and inner speech, a complete lack of behavioral landmarks. Some specific challenges for silent, imagined, and inner speech include: (1) difficulty distinguishing speech from non-speech activity, (2) a lack of temporal information about the speech content, and (3) difficulty for study participants to utter silent speech [14] due to the absence of auditory feedback. Another confound for silent speech is that articulation may change depending on the communication situation: e.g., a silent speaker communicating in a public place may hypo-articulate to prevent lip-reading and maintain privacy. Careful instruction of study participants is therefore necessary to obtain consistent signals.

III. CAPTURING SPEECH-RELATED BIOSIGNALS

This section describes the production of speech as a result of (1) respiratory, laryngeal, and articulatory activity, (2) intraoral residual acoustic activity, (3) muscle activity, and (4) brain activity, and gives an overview of methods and techniques for their acquisition, (see step #2 in Figure 1).

A. Respiratory, Laryngeal, and Articulatory Activity

Breathing is central to speech production by providing the airflow required to generate sounds. Breathing kinematics can be recorded by means of a face/nose mask or by chest and abdominal plethysmography; their properties during speech production have been extensively studied for more than 40 years (e.g., [15]). More recently, Rochet-Capellan et al. [16] revealed that breathing may contribute to timing and coordination between dialogue partners in face-to-face spoken communication.

Laryngeal activity refers to vocal fold oscillations (in modal and murmured speech), and can be estimated either indirectly from speech acoustics using inverse filtering, or directly by an electroglottography (EGG) [17]. With EGG, the degree and rate of vocal fold contact is related to changes in electrical resistance between two electrodes placed around the neck. This technique is very sensitive to the exact positioning of the electrodes relative to the location of the vocal folds.

Articulatory activity refers to the movements of the speech articulators, and can be measured using a number of different techniques. Here, we distinguish techniques based on sensors attached along the vocal tract from imaging techniques.

Magnetic Articulography (EMA/PMA): Two techniques *Electromagnetic Articulography* (EMA) [18] and *Permanent-Magnetic Articulography* (PMA) [19], [20] are available to measure articulator configurations during speech production using magnetic field sensing. The location where magnetic field generation and sensing take place differentiates each approach.

To record EMA, participants are seated with their head inside an alternating magnetic field, generated by transmitter coils. This field induces an electrical current in receiver coils glued to the main articulators (tongue, lips, velum). Multiple transmitter and receiver coils are used to recover real-time articulatory movements in a 2D or 3D Cartesian space. EMA records articulatory data with very high spatial and temporal resolution (<1 mm, ~500 Hz), and is used to model articulatory dynamics during speech production. These data have been explored in different areas of speech technology, such as automatic speech recognition [21], low bit-rate speech coding [22], and speech synthesis [23]. EMA is an invasive procedure and requires wires to be run inside the mouth, which can cause discomfort, and is not portable. As a result, EMA is typically used in laboratory settings.

In PMA, the positions of the sensors are reversed: permanent magnet transmitters are attached to the articulators, and the sum magnetic field is measured by sensors outside the mouth. The resulting field is a superposition of all the transmitter fields, and requires sophisticated analyses to decode the spatial position of articulators. However, since PMA requires only permanent magnets to be fixed inside the mouth without any connecting wires, it is more comfortable than EMA [19].

Palatography: This technique uses sensors embedded inside a pseudo-palate that are placed inside the mouth. In Electropalatography (EPG), contact sensors are used to record the timing and location of palatal contacts during speech. A modification by Birkholz et al. added optical distance sensors to the pseudo-palate (Optopalatography) [24] to record tongue positions for phonemes that do not involve palatal contacts (e.g., vowels), and lip movements.

Imaging techniques (IMG): Video imaging is a straightforward way to capture the movements of the visible speech articulators (i.e., lips and jaw) during speech production. Several sizeable (audio-)visual data corpora are available, such as GRID [25] and the “Lip Reading in the Wild” corpus [26].

Medical imaging techniques can be used to capture the movements of the intraoral articulators. Magnetic Resonance Imaging (MRI) is widely used in phonetic research [27], and obtains high-contrast images of the vocal tract showing all articulators and internal structures. Moreover, recent advances in real-time dynamic MRI (RT-MRI) can be used to record sequences of vocal tract images at 100 fps with acceptable spatial resolution [28]. However, MRI requires a bulky and expensive equipment which prevents its use as a portable communication device.

Ultrasound imaging of the vocal tract is a clinically safe technique that records images of tongue movements during speech in the mid-sagittal or coronal planes with good spatial and temporal resolution (~1 mm, ~80 Hz), see [29] for a complete review. Data is recorded by placing an ultrasonic transducer beneath the chin (held manually or using a head strap) to emit ultrasonic waves and detect reflections from the upper surface of the tongue. Ultrasound images have relatively low quality due in part to the presence of speckle noise and to a loss of signal from tongue structures with poor alignment to the ultrasound beam (i.e., non-orthogonal). However, lightweight ultrasound scanners are now available making this technology suitable for practical communication systems.

B. Intraoral Acoustic Activity

The acoustic output of very soft vocal productions such as murmured speech is too small to be recorded using a conventional microphone, though it can be captured using a stethoscopic (i.e., tissue-conducted), non-audible murmur (NAM) microphone [30]. The device is placed just below the ear, and is capable of detecting very low-amplitude sounds generated inside the vocal tract by a soft laryngeal airflow. The main application for NAM microphones is the design of silent speech interfaces. Intraoral acoustic activity can also be exploited for spoken communication (in normal speech) in very noisy / adverse environments (e.g., a helicopter cockpit). Some examples include *throat microphones* that detect the acoustic variations propagating through the neck tissues [31], and *bone-conducted* microphones that detect intraoral activity via a sensor placed on the skull [32].

C. Muscle Activity

Muscular activity can be observed using electromyography (EMG) to capture electrical signals generated during muscle fiber contraction [33]. EMG can be recorded in two ways: invasively via needle electrodes inserted into muscle tissue or non-invasively using surface electrodes. Surface electrodes are most common in the context of speech processing systems since using needle electrodes requires medical expertise and hygiene precautions, and they are susceptible to dislocation when applied to moving tissue [33].

Surface Electromyography (EMG): Speech-related surface EMG is acquired using electrodes attached to the face positioned either over specific muscles [34], [35] or arranged in a grid [36]. Signals are acquired as a potential difference between two electrodes, measured either in a monopolar (reference-versus-active) or bipolar (active-versus-active) configuration. The recorded voltage potentials are separated from their generators (i.e., motor units) by layers of tissue with varying conductivity; therefore, they represent a superposition of many activity sources, possibly even several muscles. The EMG signal is further attenuated by skin tissue and the skin-electrode interface, which both act as a low-pass filter [37]. However, EMG is advantageous for speech synthesis and recognition because the signal appears approximately 60 ms *before* actual articulatory movements [38], [39].

D. Brain Activity

Brain activity can be measured based on its hemodynamic (fMRI, fNIRS) or electrophysiological (EEG, MEG, ECoG, microelectrodes) dynamics.

Functional Magnetic Resonance Imaging (fMRI): Neural activity can be acquired using fMRI by observing the changing concentrations of oxygenated and deoxygenated hemoglobin, which are related to the increased demand for oxygen as neurons are active and engaged. Oxygenated and deoxygenated hemoglobin have different magnetic properties that can be detected by the strong magnetic fields produced in the MRI environment. Due to its high spatial resolution over the entire brain, fMRI is the de-facto standard in neuroimaging and has been instrumental in a variety of studies investigating speech and language, for reference, see [40] for a review. The slow nature of the hemodynamic response, noisy environment, and the large chamber required for fMRI significantly limits the utility for practical communication interfaces.

Functional Near Infrared Spectroscopy (fNIRS): fNIRS is a brain imaging technique pioneered by Jobsis [41] that also detects changes in the amount of hemoglobin present in the brain as an indirect marker of neural activity. Light in the near infrared spectrum is absorbed by hemoglobin, but not by biological tissue (e.g., bones, skin, muscle). Therefore, the amount of hemoglobin present can be estimated by placing near infrared light emitters and detectors around the head and calculating the amount of light absorbed. Similar to fMRI paradigms, neural activity increases the demand for energy, which is supplied by fresh oxygenated blood that carries hemoglobin to the site of neural processing. fNIRS is well suited to investigate speech processes in non-clinical populations as it is less affected by motion artifacts that plague EEG [42] and can quickly be set up in non-laboratory environments. fNIRS emitters can also be easily realized using LEDs [43], which enable low-cost fNIRS devices [44]. Additionally, the light emitters and detectors do not require additional skin preparation steps common to EEG (e.g., skin abrasion and application of conductive gel), which simplifies acquisition.

Electroencephalography (EEG): EEG is the measurement of the electrical activity of the brain using electrodes placed on the surface of the scalp. EEG signals observed at individual electrode sites are the result of the simultaneous activation of millions of neurons whose summed voltage is conducted through the brain volume, skull, and scalp layers [45]. The large number of neurons contributing to the EEG signal, combined with the low-pass filter properties of the skull and scalp, result in a spatial resolution on the order of centimeters and spectral bandwidth on the order of 80 Hz. As a non-invasive measure of electrophysiological activity, EEG has desirable temporal properties to adequately characterize the neural processing of speech production. Unfortunately, EEG is highly susceptible to myoelectrical, motion, and environmental artifacts, which interfere with EEG recordings made during overt speech production (e.g., modal, whispered, and silent speech) [46]. Though some methods have been developed to cancel this interference (e.g., [47]), validation is still needed to ensure only artifacts are removed from the EEG signal. An alternative is to record EEG during imagined speech (see Table III), or to restrict analysis to the speech motor planning and preparation phases (e.g., [48]). See [49] for a comprehensive review of the EEG components involved in speech and language processing.

EEG is typically recorded and processed using time-locked averages (i.e., event-related potentials, ERPs) to overcome its comparatively low signal-to-noise ratio [50]. However, EEG can also be analyzed as single-trial ERPs and for changes in spectral content over time (e.g., event-related (de)synchronization) [51]. Despite the disadvantages for studying speech, EEG remains the most common technique used in BCIs for communication [1].

Microwire Electrodes & Microarrays: Intracranial wire microelectrodes and microarrays, such as the Utah array [52], provide unparalleled spatial and temporal resolution down to single neuron action potentials. The electrodes are typically 1–2 mm long and have recording surfaces that range from 20 – 80 microns [53]. They record extracellular potentials of only those neurons nearest to the recording tip, and as an array they can record small brain areas of a few square millimeters simultaneously. Extracellular recordings contain both neural spiking data (action potentials, 300 – 6000 Hz) and the local field potential ($<$300 Hz), which represents the neural activity from a larger area around the electrode tip [54].

The invasive procedure to implant microarrays or microwire electrodes into the cortex is only rarely performed with humans and few studies exist investigating speech processes using this technique. In these few examples, implants in cortical areas for speech-motor control have been used to analyze and decode intended phone production [55], [56], and to control a vowel speech synthesizer [57], [58].

Electrocorticography (ECoG): ECoG is an invasive technique for measuring the electrical activity of the brain from sites directly on the cortical surface. The opportunity to measure ECoG in humans is most common in patients with severe cases of epilepsy, who require temporary implantation of electrode grids for pre-surgical planning, or intra-operative monitoring [59]. The implanted sub-dural electrode grids can remain on the brain surface for a period of several days to two weeks, during which patients consent to participate in scientific experiments.

Clinical ECoG recordings typically have an electrode spacing on the order of 10 mm, while micro-ECoG recordings can have spacing on the order of 1 mm. In contrast to scalp EEG, ECoG signals measured on the brain surface do not suffer from spatial blurring from dura matter, skull, and scalp [60], record electrical activity from neural tissue directly underneath each electrode, and are less susceptible to muscle and environmental artifacts. ECoG recordings have a spectral bandwidth in excess of 200 Hz, and special emphasis has been placed on the high-gamma band ($>$70 Hz), which is not readily observable in scalp EEG [61]. The high-gamma range is very spatially localized and highly correlated with cognitive functions and behavioral output, including speech processes [62].

IV. Processing Biosignals for Spoken Communication

While the analysis of the described speech-related biosignals can be used to gain a better understanding of speech processes in general, the development of biosignal-based applications for spoken communication requires further processing (see step #3 of Figure 1). Biosignals are first processed to extract suitable features and to handle artifacts, followed by classification or regression methods to generate the output for the targeted application. The classification approach typically consists of using automatic speech recognition for the transformation of spoken commands or continuous speech into text (e.g., phones, words, phrases or complete sentences), which then can be displayed on a screen or synthesized using text-to-speech synthesis. The regression method typically involves using speech synthesis for the direct mapping of biosignal-captured spoken input to audible speech output. While the boundaries between these three steps are sometimes blurred in practice, for simplicity, we describe them separately. Thus, this section starts with a summary of feature extraction methods for each biosignal, followed by short overviews of speech recognition and synthesis approaches applied to biosignal-based spoken communication with emphasis on the peculiarities of non-acoustic speech-related biosignals. Finally, we summarize the current status of these systems and discuss open challenges.

A. Extracting Relevant Features from Biosignals

Following the acquisition of speech-related biosignals (Section III), relevant features are extracted according to mode-specific standards in physiological signal processing.

Acoustic signals, limited here to body conduction microphones (including NAM), are typically processed similarly to standard speech signals from normal (modal) speech. For example, Mel-Frequency Cepstral Coefficients (MFCC) plus context features can be estimated from NAM recordings [30].

Visual articulatory data (e.g., video images of the lips, ultrasound images of the tongue, etc.) are usually acquired as high-resolution 2D or 3D data. We briefly review three main approaches that have been investigated in the context of audio-visual and visual-only speech recognition, silent speech interfaces, and articulatory biofeedback. See [63] for a more detailed review.

In one approach, automatic segmentation of the articulators in each video image (i.e., the extraction of their contours) has been used to track lip movements using the active shape model (ASM) [64], active appearance model (AAM) [65], and more recently constrained local neural fields (CLNF) [66]. For ultrasound images, the robust and fully automatic tracking of the tongue is still an unsolved issue and has been investigated using ASM [67], AAM [68], and neural networks (shallow [69], deep [70]). A second approach uses dimensionality reduction techniques in which an entire region-of-interest is processed without focusing on a particular object (e.g., lip or tongue contours). Some examples of this approach include the discrete cosine transform to process lip images [71] and principal components analysis for lip [72], and tongue images [73]. A third approach has recently emerged using the deep learning paradigm in which both discriminative feature extraction and classification can be jointly achieved. One powerful deep architecture is the so-called *Convolutional Neural Network* (CNN) [74], which has been used in a few recent studies for encoding lips [75], and for extracting high-level articulatory abstractions from the joint observation of lips and tongue images [76].

Magnetic-articulography techniques (i.e., EMA or PMA) commonly provide a low-dimensional data vector representing the positions of the speech articulators, and requires only minimal pre-processing. EMA systems directly measure the 2D or 3D coordinates of the receiver coils attached to the articulators, and are usable in raw form by a classifier or a regression model. PMA data are less explicit and may require more preprocessing such as low-pass filtering, background cancellation, and normalization for proper identification of articulatory positions and movements [19].

Palatography (i.e., EPG and OPG) EPG provides an exact 2D plus time representation of tongue-palate contact patterns and does not require any post-processing. Additional procedures are required for OPG in order to calibrate the distance sensors (the user must touch each sensor once with the tongue while the pseudopalate is in the mouth) and to compensate for measurement errors made when the tongue is not oriented perpendicular to the axes of the optical sensors [77]. Once completed, no further data post-processing is required.

Electromyography provides a timecourse of muscular activation for each recording electrode. Initial approaches used simple thresholding techniques [78] and comparisons of whole-word EMG averages between channels [79] to identify muscles active during speech. Modern approaches now use *time-domain* features [39] similar to the *Hudgins* feature set [80] and *spectral* features [81], [34], [82], [35], [83].

Hemodynamic responses measured by fMRI and fNIRS depend on metabolic processes and are relatively slow as a result. Simple features such as the linear data trend well describe neural activity in fNIRS [84], and newer approaches subsample the hemodynamic response and employ classification methods to determine information bearing spatio-temporal filters [85].

Electrical brain signals measured by EEG and ECoG use similar techniques for analyzing their respective signals to describe the neural processes underlying speech production, and focus on spatial, temporal, and spectral properties. With EEG, it is common to apply a bandpass filter from 1–30 Hz since signals $>$30 Hz are often unreliable due to low SNR. After filtering, ERPs can be aligned to the onset of speech production and averaged to focus on either the time periods preceding or following production onset. The times preceding speech have been well studied and have revealed two major slow-wave potentials that systematically vary with speech production: (1) the *bereitschaftspotential (BP)*, a negativity that occurs in the 1–2 s prior to self-paced speech production [48], and (2) the *contingent negative variation*, a negativity that occurs prior to cued speech production [86]. Analysis of the intervals during speech production is difficult due to EMG contamination (cf. [46]); Alternatively, EEG can be used to intepret neural processes involved in cued imagined speech using both the broadband (1–30 Hz) ERP [87] and narrowband (alpha, beta, and theta) power modulations [88]. The amplitude envelope of the high-gamma band (>70 Hz) in ECoG closely tracks aspects of the acoustic speech signal and can provide an even more detailed view of the spatio-temporal progression of brain activity during speech processes [3], [89]. Similar analyses can be applied to microarray recordings using features such as rate codes and tuning curves [55], [56].

B. Biosignal-based Speech Recognition

Automatic speech recognition (ASR) systems convert speech (typically audio) into text, i.e., a sequence of written words. The ASR task is characterized by its multi-level sequential nature: small units, usually (context-dependent) phones, are concatenated into words, which in turn are concatenated into continuous sentences. In addition, prior probabilities are assigned to word sequences by means of *language models*. For more than 30 years ASR has been dominated by multi-level statistical modeling schemes, in particular hidden Markov models (HMMs) [90] and n-gram language models [91]. Recent applications of artificial neural networks have revolutionized ASR with the development of hybrid Deep Neural Network Hidden Markov Model systems [92], and end-to-end systems that directly map speech features into text [93].

Fundamentally, biosignal-based speech recognition can be approached by replacing the acoustic signal processing front-end with methods tailored to each biosignal while leaving the statistical modeling back-end unchanged. Examples of this approach include isolated word recognition using image-specific features for lipreading [94], and continuous phone-based HMM recognition using sEMG signals [39]. However, there are interdependencies at each processing level in the speech recognition pipeline that allow for adaptation / improvement to back-end systems for each biosignal.

One important design aspect of biosignal-based speech recognition is the way in which smaller units are concatenated into words and sentences. Large units may be easier to recognize, but harder to share between different words, leading to difficulty recognizing unseen vocabulary and additional training data requirements. Short units may be unstable due to coarticulatory effects, or they might not contain enough information to reliably identify a pattern of articulation. In visual speech recognition, *viseme* units have been defined by visually grouping phones of similar appearance, or by considering articulatory gestures [95]. However, speech recognition with visemes causes ambiguities that must be resolved, e.g., by language models. *Bundled Phonetic Features* [96] are a data-driven approach that has been successful for EMG-based speech recognition. Finally, biosignal-based speech recognition has been explored using syllables [97] and context-independent or context-dependent phones [98], [99], [100].

In multi-modal speech recognition, combining sources of information is of particular interest, both for recognition and for possible audio-based bootstrapping. The reliability of each biosignal modality is highly variable, depending on phonetic properties [101] and on the environmental conditions (e.g., noise). Frameworks for dynamic estimation of stream weights have been developed for audio-visual and audio-plus-myoelectric speech recognition [102], [103]. Furthermore, manifestations of the articulation (e.g., brain signal, EMG onset, visible muscle contraction, and sound) are not synchronous [72], [39] due to the multi-step nature of speech motor control and the complex relation between articulatory gestures and speech sounds [104], [105]. Articulatory information (place, manner voicing) can also be used to augment conventional (i.e., audio-based) ASR. Incorporating explicit speech production knowledge in ASR can improve the recognition of spontaneous speech and increase robustness to noise, by modeling more efficiently some co-articulation effects, see [106] for a complete review on this line of research.

Visual articulatory data: Audiovisual speech recognition (AVSR) combines video of a speaker's lips / face with traditional speech audio signals to improve ASR performance in adverse conditions (i.e., background noise) [107]. AVSR continues to be widely investigated (see [108] for a complete review) and has been extended to *purely visual* speech recognition (VSR). In that case, no audio signal is used and speech recognition is performed only from visual information. Lip movements observable by video provide only partial information on speech articulation; therefore, recent efforts have also explored the combination of video and ultrasound imaging to capture both lip and tongue movements [109].

Similar to audio-based speech recognition, classification in AVSR or VSR systems is often accomplished using models that explicitly account for speech dynamics including: HMM [110], [94], [99], deep neural networks [111] and long short-term memory neural networks [112]. Though the addition of visual to audio modalities can augment speech representations, they may be acquired with different temporal structures that must be reconciled, e.g., coupled-HMM [113] and dynamic Bayesian network [114].

Magnetic articulography: Automatic continuous speech recognition from EMA data have been investigated for English [115] and French [116] (in conjunction with the audio signal), and small vocabulary recognition using PMA [117] using standard ASR techniques.

Electromyographic signals: Early EMG-based speech recognition used just three surface EMG electrodes to discriminate Japanese vowels [78] and has since been combined with auditory signals for better performance in noisy environments [118]. More recently, EMG-based recognition has been applied to silent speech applications [81], including whole phrases spoken in silent and normal modal speech [34], [39], syllables [97], and phones [100]. Further developments include modeling context-dependent *Bundled Phonetic Features* to address data sparsity [96], adaptation to cope with recording session discrepancies [119], and development of a hybrid neural network – HMM system for EMG-based ASR [120].

Hemodynamic responses: Both fMRI and fNIRS have mostly been used to study speech neuroscience examining the averaged hemodynamic responses over many repetitions of speech tasks. However, a successful silent speech interface must be able to detect speech events in a single trial. A few studies have investigated this decoding approach using fMRI for decoding three Dutch vowels [121], nouns [122], and functional representations of natural speech [123]. Initial applications of fNIRS to speech recognition have focused on discriminating between the speech modes: modal, silent, and imagined [124], [125]. Using fNIRS, these modes can be discriminated from each other and from intervals without speech activity in single trial. However, the slow nature of the hemodynamic response prohibits investigation on a more fine-grained time scale than whole sentences, and thus does not scale up to spoken communication in any speaking style.

Electrical brain signals: The earliest attempts for speech recognition in EEG were used to predict the word a participant was attending to in a passive listening paradigm, without any speaking involvement (silent, imagined, or other) [126]. This approach has been improved using ECoG to reconstruct a stimulus from auditory cortical activity during passive listening [127]. Additional attempts have focused on speech production (actual or imagined) paradigms for decoding acoustic features and phonemes (EEG: [87], [128], [129]; ECoG: [130], [131]; microelectrodes: [55], [56]), syllables (EEG: [88]; ECoG: [132]), and words (ECoG: [133]). ECoG has also been used to decode speech articulatory features [134], and recently HMM-based ASR was applied to ECoG signals to decode continuously spoken speech [98].

C. Biosignal-based Speech Synthesis

In contrast to speech recognition approaches, speech synthesis is a means to artificially produce human speech from a given input signal. Current biosignal-based approaches usually consist of three processing steps: (1) features extraction from biosignals and (intended) speech (e.g., Mel-cepstral features), (2) biosignal features are mapped to speech features, and (3) speech is synthesized from the predicted speech features, for example by a *vocoder* (a digital filter that models the spectral envelope and is excited with a proper signal). In this section we focus on the second step.

The mapping between biosignal and speech features is usually described as a regression problem between multidimensional continuous variables. Gaussian Mixture Regression is a classical approach inspired by statistical voice conversion [135], [136] and has been used for EMG [137], PMA [20] and US [138] applications. Specifically, the joint probability density function of biosignal inputs and speech outputs is modeled by a Gaussian Mixture Model (GMM). The mapping from biosignal to speech is accomplished either frame-by-frame using the conventional mean square error estimator [135], or sequence-by-sequence using a maximum-likelihood estimator [136]. Artificial Neural Networks are also powerful regressors that can be used for direct biosignal-to-speech mapping, and have been used for EMA-to-speech [139], [140], EMG-to-speech [141], and ultrasound/video-to-speech [73]. An HMM-based regression technique based on full-covariance GMM has been proposed to explicitly model phoneme-specific dynamics of articulation, and to use linguistic priors for regularizing biosignal-to-speech conversion [138]. A performance comparison of different mapping approaches in terms of real-time capabilities and conversion quality has been carried out for EMG-to-speech in [142].

Brain-based biosignals have primarily been used for speech recognition applications (Section IV-B), and do not directly incorporate speech synthesis into their decoding models. Only very few attempts have been made for direct speech synthesis using electrophysiological signals from the human brain. In one example, a microelectrode device implanted into the speech motor cortex was used to control a formant frequency speech synthesizer [57], [58]. This BCI-speech synthesizer converted changes in neural activity into the first two formant frequencies using an adaptive filter neural decoder, followed by synthesis for immediate audio output. A recent study has extended the BCI-based formant synthesizer technique for use with EEG instead of implanted microelectrodes [143]. ECoG has also been used for direct synthesis BCIs by applying regression methods to reconstruct the speech spectrogram which can then be converted to an audio waveform [144].

Finally, we note that biosignal-based speech synthesis can be achieved by performing speech recognition followed by applying conventional text-to-speech systems. This method produces high-quality output, but is constrained by the limitations of the underlying recognizer. In particular, speech recognition operates on limited vocabulary, produces recognition errors, and there is an unavoidable delay between articulation and synthesis since words must be completely articulated and recognized before synthesis is possible. This delay is often undesired, particularly in biofeedback applications (see section V-B), which encourages further work on direct speech synthesis from biosignals.

D. Current Research and Open Challenges

All systems described above have made substantial progress in recent years, particularly in algorithm improvements, system miniaturization, and field studies. This section summarizes the status of different biosignal processing systems, their current applicability, and open challenges identified from both the literature and our own work.

The reviewed technologies can be grouped into two categories based on their practical applicability and maturity: (i) a stable baseline system is being tested in field studies with a *substantial* number of potential users (including patients where applicable); (ii) studies are performed on a small number of subjects under laboratory conditions. Technology in category (i) must necessarily provide an easy-to-use recording system and a reasonable speech recognition / synthesis quality.

Visual articulatory data are typically in category (i); large visual speech corpora exist and have been used in various AVSR and VSR studies [111], [112], [26], benefiting from the fact that data can be recorded without special equipment, or is already available. One study achieved 65.4% word accuracy for the recognition of 333 word classes *without* use of a language model applying television broadcasts data [26]. This result is considered state-of-the-art given the large variation in the data and the size of the vocabulary. Yet, improvements can be made considering that short words were excluded due to the presence of visual ambiguities.

EMG-based speech recognition is also considered in category (i); it has been used with large amounts of data from many subjects [145] and has even been extended to speech restoration applications for individuals with laryngectomies [83]. Also, PMA-based speech recognition [117] and EMA-based speech synthesis [140] have been successfully applied to speech restoration, and EPG-based biofeedback to speech therapy [146]. Recognition accuracy has sufficiently improved for feasibility in basic communication scenarios using EMG, e.g., Word Error Rate of 10.3% on a 2000-word vocabulary [83]. In addition, EMG recording systems are mobile and non-intrusive, though it requires time and experience to properly attach the recording electrodes, and best results are obtained when training and test data are recorded in *one* session, without intermediate removal of the electrodes. Unsupervised adaptation schemes show potential to compensate for these session dependencies [119].

Speech recognition from electrical brain signals has so far been limited to laboratory environments (category (ii)), due to methodological complexity and in some cases surgical intervention is required to be performed in specialized hospital environments (e.g., ECoG). Progress using hemodynamic approaches is limited by portability constraints and limited temporal resolution of metabolic processes (e.g., fMIR, fNIRS).

Research foci in biosignal-based speech processing naturally follow from the observed limitations of the existing systems, and include the following:

- *Robust and Portable Recording systems*: Portability has been achieved for PMA [20], EMG [34], and to some extent video/ultrasound [138]. In the case of lipreading, a system could also be based on fixed cameras (e.g., for forensic purposes) instead of a personal device, but this only works if there is an unobstructed view of the subject's face. EEG data can in theory be obtained with a portable device, however in practice high-quality signals are only obtained under laboratory conditions. ECoG, as described above, requires a specialized hospital environment.
- *Feedback*: In Section II-B we note that silent, imagined, and inner speech may be difficult to utter reliably and consistently. Real-time feedback [57], [140], is considered a promising approach to resolve this issue, though it is both a technical challenge (since data must be processed very quickly) and a modeling challenge (due to the asynchronicity between different manifestations of the speech process, see section IV-B).
- *System Adaptation for Silent or Inner/Imagined Speech*: Instead of relying on speakers to properly use real-time feedback, an alternative approach proposes algorithmic adaptation to account for variability in speaking modes, as has been done for an EMG-based speech recognizer [147], [148]. While discrimination of speaking modes from brain activity has been shown to be possible [124], understanding the difference between modal and imagined speech processes and creating large-scale recognizers for imagined speech are still significant open issues.
- *Multi-Session and Multi-Speaker systems*: Most existing systems are speaker-specific, with the exception of some lipreading systems [26]. Even when data is only taken from one speaker, there may be inter-session differences due to a variety of factors (e.g., environmental artifacts, sensor positioning, etc.), which can be remedied by standard methods (adaptation [119], recalibration [140], integration of session independence as a neural network training objective [149]).
- *Sufficiency of speech representations*: Visual speech recognition using only lip images (i.e., lipreading) is insufficient, and suffers from ambiguities, which can be resolved by including ultrasound images of the vocal tract as an additional input. EMA/PMA and EMG are more sufficient, though EMA/PMA do not represent facial gestures, and without needle electrodes, EMG can not represent specific tongue muscles. That said, these methods provide a fairly complete representation of the speech process with ambiguities in voicing only (cf. [101]). Acquiring appropriate and sufficient signals directly from the speech- and language-related areas of the brain should also provide a complete representation of the processes needed to understand and generate speech, though there is a practical limit on signal acquisition and interpretation. For brain-based techniques, sufficiently sampling the speech and language-related areas of the brain remains an open and intriguing challenge.

A comparison between biosignal-based speech processing systems is difficult at this time since available data corpora differ in size, vocabulary, recording setup, etc., and benchmark data have not been established yet. For speech recognition with medium-sized vocabularies, the three major articulation-based systems (PMA, video+ultrasound, EMG) all perform reasonably and similarly, and further improvements are likely in the near future. The availability of large data corpora will be crucial in extending these systems to truly large-scale speech recognition (with tens of thousands of vocabulary words), and equally to high-quality speech synthesis. Ultimately, the "best" system will be the one which most convincingly resolves the issues summarized above, and will depend upon the constraints of the intended application, including factors such as user preference, performance, reliability, environment, comfort, aesthetics, etc., see section V.

V. Use Cases of Biosignal-based Spoken Communication

Capturing, processing, and interpretation of biosignals related to speech in the absence of an intelligible airborne acoustic signal opens up novel use cases in spoken communication (see step # 4 in Figure 1). A survey on Silent Speech Interfaces (SSI) [4] introduced relevant human-computer interfaces developed before 2010. Sensor technologies and machine learning advanced this field in the past few years. Published use cases and applications of "Biosignal-based Spoken Communication" fall into four main categories, (1) voice prostheses and devices to *restore spoken communication*, for individuals unable to speak due to impairment, disease, or accident; (2) methods to deliver articulatory biofeedback of voice production to increase articulatory awareness for *therapy and training for spoken communication*, such as speech therapy and language learning; (3) approaches to enhance speech recognition and synthesis performance for *robust spoken communication in noisy environments*, like the fusion of complementary speech-related biosignals to compensate for signal corruptions under adverse noise conditions; and (4) strategies for *mute spoken communication* in situations, when audible communication is prohibited or unwanted, e.g., avoiding disruptions in quiet environments or securing against eavesdropping. The concrete systems which we describe in this section frequently address several of these challenges, but often target just a single application. This strategic approach affects the direction of research, requires diverse ethical considerations (e.g., for working with patients), and also influences the design of the communication system: for example, individuals with speech impairments may be willing to invest a significant amount of time into the optimization of their personal communication system, whereas healthy users typically expect little or no enrollment time.

A. Restoring Spoken Communication

An important goal for biosignal-based speech synthesis techniques is to restore spoken communication for individuals with disordered or absent vocalization. Each of the modalities described has specific applications and is most appropriate for specific clinical populations (e.g., individuals with dysarthria, laryngectomy, or paralysis). In laryngectomy, an individual's larynx is surgically removed, and traditional options to restore voice include: using an electrolarynx device resulting in a very robotic voice, using oesophageal speech, or using a tracheosophageal prosthesis, which has to be replaced every few months. Biosignal-based alternatives for this population include PMA-synthesis [19], [117] and EMG-based speech recognition [83].

For individuals with the most severe speech and motor impairments, the objective is to supplement or bypass the speech-motor pathways using available biosignals for improved speech output. In this use case, current research focuses on synthesizing speech during imagined speech, or speech attempts by individuals with total paralysis, directly from brain signal recordings. The superior spatial resolution and signal fidelity of invasive techniques such as microelectrodes and ECoG make them promising approaches for the design of practical speech-based BCIs and neuroprosthetics [57], [58], [98]. Such systems may perform a continuous reconstruction of speech or a discrete classification and output of sounds, words, etc. (see Section IV-B), depending on the objective and constraints of the system. While it may be possible to decode individual words or phrases discretely, scaling this approach to a larger vocabulary can become intractable. Alternatively, the ability to decode basic units of speech, such as formants or phones [98], will enable the creation of generative models that are not limited to a fixed vocabulary. In any case, effectively developing and transferring models trained on normal modal speech to imagined speech remains an active research challenge since the neural representations of normal modal and imagined speech are not identical.

B. Therapy and Training for Spoken Communication

The methods developed for biosignal-based speech processing can also be used for multimodal biofeedback in order to study speech production, facilitate second language learning, and rehabilitate speech impairments. Visual feedback of the articulators (e.g., lip reading) can have a dramatic effect on perception [150], and can even improve speech perception and comprehension by individuals with hearing impairments [5]. Articulatory kinematics captured using EMA have been used for speech training with an emphasis on improving second language learning [6], and investigating articulatory deficits in dysarthria [7]. EPG has also been successfully used as a biofeedback tool for speech therapy [146] and L2 pronunciation training [151]. Promising results using ultrasound imaging have also been obtained for rehabilitation of the English /r/ [152] and persisting speech sound disorders [153].

Notably, biosignal-based speech recognition and synthesis performance declines for silent compared to normal speaking, even when the ASR system is trained and tested exclusively on the respective speaking modes [148]. Speakers report difficulties to steadily producing silent speech [14], in part due to the absence of auditory feedback that is critical for normal speech production [154], [155]. Biofeedback created by real-time speech output could provide an optimal solution to alleviate the challenges in BCI and SSI (see section V-D below). In a closed-loop paradigm, speakers can rely on synthetic speech for auditory feedback and exploit it to regulate their own production, as in [140] for SSI and [57] for BCI.

C. Robust Spoken Communication in Noisy Environments

Improving spoken communication under adverse noise conditions has long been a challenge for speech research and development. Large-scale DARPA programs (e.g., ASE, SPINE, RATS) targeted improvements to speech processing in military and civilian contexts, such as in combat situations, air traffic control, search-and-rescue operations, and security scenarios. Beside the development of noise-robust algorithms, this led to the creation of new sensors like throat and bone-conduction microphones, which can be combined with traditional microphones for improved, fused biosignal ASR [156]. EMG is a natural extension of these techniques and has been used for small vocabulary recognition in acoustically harsh environments [157], and spoken communication for firefighters, pilots, and astronauts through electrodes integrated into self-contained breathing apparatuses [81], [158]. Like subaudible microphones, the EMG combined with conventional acoustic signals can further improve ASR performance in noisy environments [118].

D. Mute-Spoken Communication

In many situations, spoken communication is desired but making any sounds is prohibited or socially inappropriate. For example, carrying out phone conversations may disturb bystanders in quiet environments like libraries or is inappropriate during group meetings. Eavesdropping is a risk when communicating private information in public places. Furthermore, safety and security settings may require a silent communication. Several different biosignal-based systems address the challenges of mute-spoken communication. For instance, silent speech interfaces have been developed using ultrasound imaging, combined with a conventional video camera to capture tongue and lip movements simultaneously, without any audio signals [109], [138]. Importantly, several studies show that performance drops when speaking modes are mixed in training and testing [138]. In the case of surface electromyography, signal-based adaptation methods are proposed to reduce the differences between speaking modes [147] and EMG-based speech recognizers are designed which are trained *and* tested on silent speech [148], [35]. Another way to alleviate the impact of articulatory differences between modal and silent speech is to provide a silent speaker with a synthetic auditory feedback, in real-time [140], [57]. One example involves an articulatory synthesizer that converts EMA data into spectral features using a deep neural network, and can be controlled in real-time by naive subjects articulating silently [140].

PMA-based speech recognition and synthesis has now been achieved in a highly portable manner [20]. While most published research focuses on the aim of restoring speech communication to speech-impaired persons (see section V-A above), PMA was originally proposed for mute communication of individuals without impairment [117]. However, a full study on using silent speech to drive a PMA-based synthesizer has not yet been published.

Studies toward EEG-based speech recognition on silent or imagined speech include classification of single phonemes [87], [88], [129]. Alternative approaches use limb motor imagery to control a formant frequency speech synthesizer without the presence of an acoustic speech signal [143]. Imagined speech decoding has been accomplished with a greater range of speech output using intracortical recording methods including formant frequency prediction using microelectrodes [57], [58], phoneme classification with microelectrodes [55], spectrotemporal features using ECoG [159], and word pairs using ECoG [160].

Beyond mute communication, the technologies described in this survey may be combined with speech translation to bridge the language barrier [39]. Using current procedures, simultaneous translation of a spoken conversation results in the overlap of two voices (one voice from the speaker in the source language and one voice in the target language, coming either from a human interpreter or from the synthesized output of a speech translation system). To avoid such inconvenient scenarios, speakers could instead silently speak (or imagine) in their native tongue, while listeners hear only the translated output. Thus, the combination of mute communication plus translation creates the illusion of speaking in a foreign tongue.

VI. Conclusions and Perspectives

Biosignal-based Spoken Communication is a rapidly evolving cross-disciplinary field. Research and development takes place at the intersection of engineering, computer science, medicine, psychology, and neurosciences. It requires the mastering of sensor technologies, signal, speech and language processing, as well as human-machine interfaces.

This survey paper is intended to provide an entry point for readers interested in this very active field, to define and describe terminology, to recite relevant publications, and thereby to bridge the gap between disciplines. It presents a broad overview over the state-of-the-art technologies, methods, and applications. Table IV summarizes the applicability of biosignals for use cases and speaking modes described in this survey (table cells are grayed out for those speaking modes prohibited by a certain use case). Cell entries in normal font identify techniques that have been reported for capturing speech-related activities of the respective speaking mode and have successfully applied the resulting biosignals to the use cases; these studies are cited in this survey. Italic font indicates applicability but no published results yet, while "-" mark cases when a capturing technique is not applicable.

TABLE IV
APPLICABLE TECHNOLOGIES FOR USE CASES AND SPEAKING MODES (GRAYED OUT CELLS = NO TARGET SPEAKING MODE FOR USE CASE, *italic font* = APPLICABLE BUT NO PUBLICATIONS YET, "-" = NOT APPLICABLE)

Use Cases	Speaking Modes (Section II, Table 1-3)				
(Section V)	modal	murmer	whisper	silent	imagine
(A) Restore SC			*EMG* *PMA* *IMG* *ECoG*	EMG PMA *IMG* ECoG	- - - ECoG
(B) Therapy & Training	EMA EPG IMG *intraoral*	*EMA* *EPG* *IMG* *intraoral*	*EMA* *EPG* *IMG* -	EMA *EPG* *IMG* -	- - - -
(C) Robust SC	EMG *EPG* *PMA* *IMG* intraoral	EMG *EPG* *PMA* *IMG* intraoral	EMG *EPG* *PMA* *IMG* -		
(D) Mute SC		NAM		EMG EMA *PMA* IMG EEG ECoG	- - - - *EEG* ECoG
Insights in SC	All biosignals captured by described technologies including fMRI, fNIRS, MEG, and their combination				

Driven by recent advances in sensor technologies (resolution, accuracy, miniaturization, energy consumption, connectivity, mobility, and costs, to name only a few), the large attention and developments in neurosciences, and the impact of deep learning approaches to automatic speech processing, we expect major breakthroughs in the years to come.

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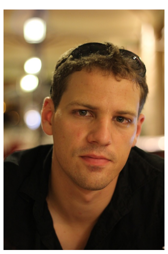

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