Perceptive, non-linear Speech Processing and Spiking Neural Networks

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Preprint of paper:
Rouat, J., Pichevar, R., Loiselle, S. (2005). Perceptive, Non-linear Speech Processing and Spiking Neural Networks. In: Chollet, G., Esposito, A., Faundez-Zanuy, M., Marinaro, M. (eds) Nonlinear Speech Modeling and Applications. NN 2004. Lecture Notes in Computer Science, vol 3445. Springer, Berlin, Heidelberg. https://doi.org/10.1007/11520153_14

Abstract. Source separation and speech recognition are very difficult in the context of noisy and corrupted speech. Most conventional techniques need huge databases to estimate speech (or noise) density probabilities to perform separation or recognition. We discuss the potential of perceptive speech analysis and processing in combination with biologically plausible neural network processors. We illustrate the potential of such non-linear processing of speech on a source separation system inspired by an Auditory Scene Analysis paradigm. We also discuss a potential application in speech recognition.

keywords: Auditory modelling, Source separation, Amplitude Modulation, Auditory Scene Analysis, Spiking Neurons, Temporal Correlation, Multiplicative Synapses, Cochlear Nucleus, Corrupted Speech Processing, Rank Order Coding, Speech recognition.

1 Introduction

Processing of corrupted speech is an important research field with many applications in speech coding, transmission, recognition and audio processing. For example, speech enhancement, auditory modelling and source separation can be used to assist robots in segregating multiple speakers, to ease the automatic transcription of videos via the audio tracks, to segregate musical instruments before automatic transcription, to clean up a signal before performing speech
recognition, etc. The ideal instrumental set-up is based on the use of arrays of microphones during recording to obtain many audio channels. In that situation, very good separation can be obtained between noise and the signal of interest \cite{1,2,3} and experiments with good enhancement have been reported in speech recognition \cite{4,5,6,7,8}. Applications have been ported on mobile robots \cite{9,10,11} and have also been developped to track multiple speakers \cite{12}.

In many situations, only one channel is available to the audio engineer that still has to clean the signal and solve the separation problem. The cleaning of corrupted speech is, then, much more difficult. From the scientific literature, most of the proposed monophonic systems perform reasonably well on specific signals (generally voiced speech) but fail to efficiently segregate a broader range of signals. These relatively negative results may be overcome by combining and exchanging expertise and knowledge between engineering, psycho-acoustic, physiology and computer science. Statistical approaches like Bayesian networks, Hidden Markov Models and one microphone ICA perform reasonably well once the training dataset or the probability distributions have been suitably estimated. But these approaches usually require supervised training on huge databases and are designed for specific applications. On the other hand, perceptive and bio-inspired approaches require less training, can be unsupervised and offer strong potential even if they are less mature. In the present work we are interested in monophonic bio-inspired corrupted-speech processing approaches.

\section{Perceptive Approach}

We propose to combine knowledge from psycho-acoustics, psychology and neurophysiology to propose new non-linear processing systems for corrupted speech. From physiology we learn that the auditory system extracts simultaneous features from the underlying signal, giving birth to simultaneous multi-representation of speech. We also learn that fast and slow efferences can selectively enhance speech representations in relation to the auditory environment. This is in opposition with most conventional speech processing systems that use a systematic analysis\footnote{Systematic analysis extracts the same features independently of signal context. Frame by frame extraction of Mel Frequency Cepstrum Coefficients (MFCC) is an example of systematic analysis.} that is effective only when speech segments under the analysis window are relatively stationary and stable.

Psychology observes and attempts to explain the auditory sensations by proposing models of hearing. The interaction between sounds and their perception can be interpreted in terms of auditory environment or auditory scene analysis. We also learn from psycho-acoustics that the time structure organisation of speech and sounds is crucial in perception. In combination with physiology, suitable hearing models can also be derived from research in psycho-acoustic.
2.1 Physiology: Multiple Features

Inner and outer hair cells establish synapses with efferent and afferent fibres. The efferent projections to the inner hair cells synapse on the afferent connection, suggesting a modulation of the afferent information by the efferent system. On the contrary, other efferent fibres project directly to the outer hair cells, suggesting a direct control of the outer hair cells by the efferences. It has also been observed that all afferent fibres (inner and outer hair cells) project directly into the cochlear nucleus. The cochlear nucleus has a layered structure that preserves frequency tonotopic organisation. One finds very different neurones that respond to various features. Schreiner and Langner [13,14] have shown that the inferior colliculus of the cat contains a highly systematic topographic representation of AM parameters. Maps showing best modulation frequency have been determined. The pioneering work by Robles, Ruggero and Evans [15][16][17] reveals the importance of AM-FM coding in the peripheral auditory system along with the role of the efferent system in relation with adaptive tuning of the cochlea. Recently, small neural circuits in relation with wideband inhibitory input neurones have been observed by Arnott et al. [18] in the cochlear nucleus. These circuits, explain the response of specialised neurones to frequency position of sharp spectral notches. Pressnitzer et al. [19] have proposed another use for such networks for auditory scene analysis.

It is also known that the auditory efferent system plays a crucial role in enhancing signals in background noise [20][21][22]. Kim et al. [22] measure the effect of aging on the medial olivocochlear system and suggest that the functional decline of the medial olivocochlear system with age precedes outer hair cell degeneration. It is clear from physiology that multiple and simultaneous representations of the same input signal are observed in the cochlear nucleus [23][24]. In the remaining parts of the paper, we call these representations, auditory images. It is interesting to note that Harding and Meyer [25] propose a multi-resolution Auditory Scene Analysis that uses both high- and low-resolution representations of the auditory signal in parallel.

2.2 Cocktail-party Effect and Auditory Scene Analysis

Humans are able to segregate a desired source in a mixture of sounds (cocktail-party effect). Psycho-acoustical experiments have shown that although binaural audition may help to improve segregation performance, human beings are capable of doing the segregation even with one ear or when all sources come from the same spatial location (for instance, when someone listens to a radio broadcast) [26]. Using the knowledge acquired in visual scene analysis and by making an analogy between vision and audition, Bregman developed the key notions of Auditory Scene Analysis (ASA) [26]. Two of the most important aspects in ASA

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2 onset, chopper, primary-like, etc.

3 Other features like transients, ON, OFF responses are observed, but are not implemented in this paper.
are the segregation and grouping (or integration) of sound sources. The segregation step partitions the auditory scene into fundamental auditory elements and the grouping is the binding of these elements in order to reproduce the initial sound sources. These two stages are influenced by top-down processing (schema-driven). The aim in Computational Auditory Scene Analysis (CASA) is to develop computerised methods for solving the sound segregation problem by using psycho-acoustical cues and physiological characteristics [27, 28]. For a review see [29].

3 Spiking Neural Networks

The previous section introduced the perceptual approach to non-linear speech analysis. In this section we emphasise the computational power of spiking neurones in the context of speech and signal processing. Autonomous bio-inspired and spiking neural networks are an alternative to supervised systems. A good review on bio-inspired spiking neurones can be found in [30] and in books such as [31], [32] and [33].

3.1 Analysis and Perception

In perception, the recognition of stimuli is quasi-instantaneous, even if the information propagation speed in living neurones is slow. This phenomenon is well documented for hearing and visual systems [34] [35, 36]. It implies that neural responses are conditioned by previous events and states of the neural sub-network [37]. The understanding of the underlying mechanisms of perception in combination with that of the peripheral auditory system [38] [39] [40] [41] [42] helps the researcher in designing speech analysis modules.

3.2 Intuitive Notion of Spiking Neurones

In the case of bio-inspired neural networks, temporal sequence processing is done naturally because of the intrinsic dynamic behaviour of neurones. The pioneering work in the field of neural networks has been done by Hodgkin and Huxley (H&H) at the University of Plymouth, who proposed a mathematical description of the behaviour of the giant squid axon. Although this model is complete so far (it can predict most of the behaviours seen in simple biological neurones), it is very complex and difficult to simulate in an artificial neural network paradigm. A very simplified model of the H&H is the Leaky Integrate and Fire model (LIF) as presented in figure 2.

$I(t)$ is the sum of the current going through the capacitance plus the resistance current. The sub-threshold potential $V(t)$ is given by:

\[ V(t) = \text{subthreshold potential} \]

\[ V(t) = \text{supra-threshold potential} \]

The Hodgkin-Huxley model integrates sub-threshold, threshold and supra-threshold activity in the same set of equations. It is not the case with the LIF model.
Fig. 1. Equivalent circuit of a membrane section of the giant squid axon (from Hodgkin-Huxley, 1952). $g_{Cl}$, $g_{Na}$ and $g_{K}$ are the conductance of the membrane for respective ionic gates. $V(t)$ is the membrane potential when $I(t) = 0$ (no external input).

Fig. 2. Equivalent circuit of a leaky integrate and fire neurone. C: membrane capacitance, R: membrane resistance, V: membrane potential.
\[ I(t) = C(t) \frac{dV(t)}{dt} + \frac{V(t)}{R(t)} \]  

(1)

\( V(t) \) is the output, \( I(t) \) is the input. When \( V(t) \) crosses a predetermined threshold \( \delta(t) \), the neuron fires and emits a spike. Then \( V(t) \) is reset to \( V_r \), where \( V_r \) is the resting potential.

In this paper we use a non-linear oscillator to reproduce the behaviour of the Integrate and Fire neurone.

In the following subsections, we review some of the studies that are pertinent to speech processing and source separation in spiking neurones.

### 3.3 Formalisation of Bio-inspired Neural Networks

There are many publications which describe mathematical formalism for spiking neurones. One can cite for example the work by Maass \[43\] and his team, in which they have shown that networks of spiking neurones are computationally more powerful than the models based on McCulloch Pitts neurones. In \[37\] the authors have shown that information about the result of the computation is already present in the current neural network state long before the complete spatio-temporal input patterns have been received by the neural network. This suggests that neural networks use the temporal order of the first spikes yielding ultra-rapid computation, according to the observations by \[35\]. In \[44\] and \[45\], the authors explain how neural networks and dynamic synapses (including facilitation and depression) are equivalent to a given quadratic filter that can, thus, be approximated by a small neural system. The authors also show that any filter that can be characterised by a Volterra series can be approximated with a single layer of spiking neurones.

**Mutual information and Pattern recognition.** Among the many publications in information theory one can cite the works by Fred Rieke et al. \[46\], Sejnowski \[47\], DeWeese \[48\] and Chechik and Tishby \[49\] where it is shown that spike coding in neurones is close to optimal and that plasticity in Hebbian learning rule increases mutual information close to optimal transmission of information.

**Novelty detection.** For unsupervised systems, novelty detection is an important property that facilitates autonomy (robots can detect if stimuli is new or already seen). When associated with conditioning, novelty detection can create autonomy of the system \[50\] \[51\].

**Sequence classification.** Sequence classification is particularly interesting for speech. Recently Panchev and Wermter \[52\] have shown that synaptic plasticity can be used to perform recognition of sequences. Perrinet \[53\] and Thorpe \[36\] discuss the importance of sparse coding and rank order coding for classification of sequences.
3.4 Segregation and Integration with Binding

Neurone assemblies (groups) of spiking neurones can be used to implement segregation and fusion (integration) of objects in an auditory image representation. Usually, in signal processing, correlations (or distances) between signals are implemented with delay lines, products and summation. With spiking neurones, comparison (temporal correlation) between signals can be made without implementation of delay lines. In section 4 page 8, we use that approach by presenting auditory images to spiking neurones with dynamic synapses. Then, a spontaneous organisation appears in the network with sets of neurones firing in synchrony. Neurones with the same firing phase belong to the same auditory objects. In 1976 and 1981, the temporal correlation that performs binding was proposed by Milner [54] and independently by Malsburg [55,56,57]. Milner and Malsburg have observed that synchrony is a crucial feature to bind neurones that are associated with similar characteristics. Objects belonging to the same entity are bound together in time. In other words, synchronisation between different neurones and de-synchronisation among different regions perform the binding. To a certain extent, this property has been exploited by Bohte [58] to perform unsupervised clustering for recognition on images, by Schwartz [59] for vowel processing with spike synchrony between cochlear channels, by Hopfield [60] to propose pattern recognition with spiking neurones, by Levy et al. [61] to perform cell assembly of spiking neurones using Hebbian learning with depression. Wang and Terman [62] have proposed an efficient and robust technique for image segmentation and study its potential in CASA (Computational Auditory Scene Analysis) [28].

3.5 Example of Associative Neural Network

Alkon et al. [63] have shown that dendrites can learn associations between input sequences without knowledge about neurone outputs. They derive an image recognition application [64] from this work. The network associatively learns correlation and anti-correlation between time events occurring in pre-synaptic neurones. Those neurones synapse on the same element (same area) of a common post synaptic neurone. A learning rule modifies the cellular excitability at dendritic patches. These synaptic patches are postulated to be formed on branches of the dendritic tree of vertebrate neurones. Weights are associated to patches rather than to incoming connection. After learning, each patch characterises a pattern of activity on the input neurones. In comparison with most commonly used networks, the weights are not used to store the patterns and the comparison between patterns is based on normalised correlation instead of projections between the network input vectors and the neurone weights. Based on this type of network, a prototype vowel recognition system has been designed and preliminary results have shown that the short-time AM structure carries information that can be used for recognition of voiced speech [65]. One of the main drawbacks of that approach is that explicit encoding of reference patterns in dendritic patches of neurones is required.
3.6 Rank Order Coding

Rank Order Coding has been proposed by Simon Thorpe and his team from CERCO, Toulouse to explain the impressive performance of our visual system \cite{66,53}. The information is distributed through a large population of neurones and is represented by spikes relative timing in a single wave of action potentials. The quantity of information that can be transmitted by this type of code increases with the number of neurones in the population. For a relatively large number of neurones, the code transmission power can satisfy the needs of any visual task \cite{66}. There are advantages in using the relative order and not the exact spike latency: the strategy is easier to implement, the system is less subject to changes in intensity of the stimulus and the information is available as soon as the first spike is generated.

3.7 Summary

Bio-inspired neuronal networks are well adapted to signal processing where time is important. They can be fully unsupervised. Adaptive and unsupervised recognition of sequences is a crucial property of living neurones. Among the many properties we listed in this section, the paper implements the segregation and integration with sets of synchronous neurones. At the moment, this work does not reflect the full potential of spiking neurones and is more or less exploratory.

4 Source Separation

Most monophonic source separation systems require a priori knowledge, i.e. expert systems (explicit knowledge) or statistical approaches (implicit knowledge) \cite{29}. Most of these systems perform reasonably well only on specific signals (generally voiced speech or harmonic music) and fail to efficiently segregate a broad range of signals. Sameti \cite{67} uses Hidden Markov Models, while Roweis \cite{68,69}, and Gomez \cite{70} use Factorial Hidden Markov Models. Jang and Lee \cite{71} use Maximum A Posteriori (MAP) estimation. They all require training on huge signal databases to estimate probability models. Wang and Brown \cite{28} proposed an original bio-inspired approach that uses features obtained from correlograms and F0 (pitch frequency) in combination with an oscillatory neural network. Hu and Wang use a pitch tracking technique \cite{72} to segregate harmonic sources. Both systems are limited to harmonic signals.

We propose here to extend the bio-inspired approach to more general situations without training or prior knowledge of underlying signal properties.

4.1 Binding of Auditory Sources

Various features of speech are extracted in different areas of the brain\cite{6}. We assume here that sound segregation is a generalised classification problem, in which

\footnote{5 Prior knowledge is embodied in the representations of the acoustic signals.}

\footnote{6 AM and FM maps are observed in the colliculus of the cat, onset neurones are present in the cochlear nucleus, etc.}
we want to bind features extracted from the auditory image representations in different regions of our neural network map.

4.2 System Overview

In this work analysis and recognition are integrated. Physiology, psychoacoustic and signal processing are integrated to design a multiple sources separation system when only one audio channel is available (Fig. 3, page 9). It combines a reconstruction analysis/synthesis cochlear filterbank along with auditory image representations of audible signals with a spiking neural network. The segregation and binding of the auditory objects (coming from different sound sources) is performed by the spiking neural network (implementing the temporal correlation [54,55]) that also generates a mask to be used in conjunction with the synthesis filterbank to generate the separated sound sources.

The neural network uses third generation neural networks, where neurones are usually called spiking neurones [43]. In our implementation, neurones firing at the same instants (same firing phase) are characteristic of similar stimuli or comparable input signals. Spiking neurones, in opposition to formal neurones, have a constant firing amplitude. This coding yields noise and interference robustness while facilitating adaptive and dynamic synapses (links between neurones) for unsupervised and autonomous system design. Numerous spike timing coding schemes are possible (and observable in physiology) [73] Among them, we decided to use synchronisation and oscillatory coding schemes in combination with

7 Mask and masking refer here to a binary gain and should not be confused with the conventional definition of masking in psychoacoustics.

8 The information is coded in the firing instants.
a competitive unsupervised framework (obtained with dynamic synapses), where groups of synchronous neurones are observed. This choice has the advantage to allow design of unsupervised systems with no training (or learning) phase. To some extent, the neural network can be viewed as a map where links between neurones are dynamic. In our implementation of the \textit{temporal correlation}, two neurones with similar inputs on their dendrites will increase their soma to soma synaptic weights (dynamic synapses), forcing synchronous response. On the opposite, neurones with dissimilar dendritic inputs will have reduced soma to soma synaptic weights, yielding reduced coupling and asynchronous neural responses.

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{temporal_correlation.png}
\caption{Dynamic temporal correlation for two simultaneous sources: time evolution of the supra-threshold electrical output potential for four neurones from the second layer (output layer). \(T\) is the oscillatory period. Two sets of synchronous neurones appear (neurones 1 & 3 for source 1; neurones 2 & 4 for source 2). Plot degradations are due to JPEG coding.}
\end{figure}

Figure 4 page 10 illustrates the oscillatory response behavior of the output layer of the proposed neural network for two sources.

While conventional signal processing computation of correlations encounter difficulties in taking simultaneously into account the spatial aspect (multi-step correlation has to be evaluated), the spiking neural network is able to compute a \textit{spatio}-temporal correlation of the input signals in one step.

Compared to conventional approaches, our system does not require a priori knowledge, is not limited to harmonic signals, does not require training and does not need pitch extraction.

The architecture is also designed to handle continuous input signals (no need to segment the signal into time frames) and is based on the availability of simultaneous auditory representations of signals. Our approach is inspired by knowledge in anthropomorphic systems but is not an attempt to reproduce faithfully physiology or psychoacoustics.
4.3 Proposed System Strategy

Fig. 5. Example of a twenty-four channels CAM for a mixture of /di/ and /da/ pronounced by two speakers; mixture at $SNR = 0 \, dB$ and frame center at $t = 166 \, ms$.

Two representations are simultaneously generated: an amplitude modulation map, which we call Cochleotopic/AMtopic (CAM) Map and a Cochleotopic/Spectrotopic Map (CSM) that encodes the averaged spectral energies of the cochlear filterbank output. The first representation somewhat reproduces the AM processing performed by multipolar cells (Chopper-S) from the anteroventral cochlear nucleus [24], while the second representation could be closer to the spherical bushy cell processing from ventral cochlear nucleus [24] areas.

We assume that different sources are disjoint in the auditory image representation space and that masking (binary gain) of the undesired sources is feasible. Speech has a specific structure that is different from that of most noises and perturbations [76]. Also, when dealing with simultaneous speakers, separation is possible when preserving the time structure (the probability at a given instant $t$ to observe overlap in pitch and timbre is relatively low). Therefore, a binary gain can be used to suppress the interference (or separate all sources with adaptive masks).

4.4 Detailed Description

Signal Analysis. Our CAM/CSM generation algorithm is as follows:

1. Down-sampling to 8000 samples/s.
2. Filter the sound source using a 256-filter Bark-scaled cochlear filterbank ranging from 100 Hz to 3.6 kHz.

\[9\] To some extent, it is related to modulation spectrograms. See for example work by [74,75].
3. For CAM: Extract the envelope (AM demodulation) for channels 30-256 (400–3600 Hz); for other low frequency channels (1–29: 100–400 Hz) use raw outputs. For CSM: Nothing is done in this step.
4. Compute the STFT of the envelopes (CAM) or of the filterbank outputs (CSM) using a Hamming window.
5. To increase the spectro-temporal resolution of the STFT, find the reassigned spectrum of the STFT (this consists of applying an affine transform to the points to re-allocate the spectrum).
6. Compute the logarithm of the magnitude of the STFT. The logarithm enhances the presence of the stronger source in a given 2D frequency bin of the CAM/CSM.

For a given instant, depending on the signal, the peripheral auditory system can enhance the AM, the FM, the envelope, or the transient components of the signal.

The Neural Network.

First layer: Image segmentation. The dynamics of the neurones we use is governed by a modified version of the Van der Pol relaxation oscillator (Wang-Terman oscillators). The state-space equations for these dynamics are as follows:

\[
\frac{dx}{dt} = 3x - x^3 + 2 - y + \rho + p + S
\]

\[
\frac{dy}{dt} = \epsilon[\gamma(1 + \tanh(x/\beta)) - y]
\]

Where \( x \) is the membrane potential (output) of the neurone and \( y \) is the state for channel activation or inactivation. \( \rho \) denotes the amplitude of Gaussian noise, \( p \) is the external input to the neurone, and \( S \) is the coupling from other neurones (connections through synaptic weights). \( \epsilon, \gamma, \) and \( \beta \) are constants. The Euler integration method is used to solve the equations. The first layer is a partially connected network of relaxation oscillators. Each neurone is connected to its four neighbors. The CAM (or the CSM) is applied to the input of the neurones. Since the map is sparse, the original 256 points computed for the FFT are downsampled to 50 points. Therefore, the first layer consists of 256 x 50 neurones. The geometric interpretation of pitch (ray distance criterion) is less clear for the first 29 channels, where harmonics are usually resolved. For this reason, we

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10 Low-frequency channels are said to resolve the harmonics while others do not, suggesting a different strategy for low frequency channels.
11 Non-overlapping adjacent windows with 4ms or 32ms lengths have been tested.
12 \( \log(e_1 + e_2) \simeq \max(\log e_1, \log e_2) \) (unless \( e_1 \) and \( e_2 \) are both large and almost equal).
13 In our simulation, \( \epsilon = 0.02, \gamma = 4, \beta = 0.1 \) and \( \rho = 0.02 \).
14 Envelopes of resolved harmonics are nearly constants.
have also established long-range connections from *clear* (high frequency) zones to *confusion* (low frequency) zones. These connections exist only across the *cochlear channel number* axis in the CAM. 

The weight, \( w_{i,j,k,m}(t) \) (figure 6), between *neurone* \((i,j)\) and *neurone* \((k,m)\) of the first layer is:

\[
w_{i,j,k,m}(t) = \frac{1}{\text{Card}\{N(i,j)\}} \left(0.25 e^{\frac{\lambda |p(i,j;t)−p(k,m;t)|}{2}}\right)
\]

where \( p(i,j) \) and \( p(k,m) \) are respectively external inputs to *neurone* \((i,j)\) and *neurone* \((k,m)\) \(\in N(i,j)\). \(\text{Card}\{N(i,j)\}\) is a normalization factor and is equal to the cardinal number (number of elements) of the set \(N(i,j)\) containing neighbors connected to the *neurone* \((i,j)\) (can be equal to 4, 3 or 2 depending on the location of the neurone on the map, i.e. center, corner, etc.). The external input values are normalized. The value of \( \lambda \) depends on the dynamic range of the inputs and is set to \( \lambda = 1 \) in our case. This same weight adaptation is used for *long range clear to confusion zone* connections (Eq. 8) in the CAM processing case. The coupling \( S_{i,j} \) defined in Eq. 2 is:

\[
S_{i,j}(t) = \sum_{k,m \in N(i,j)} w_{i,j,k,m}(t)H(x(k,m;t)) − \eta G(t) + \kappa L_{i,j}(t)
\]

\( H(.) \) is the Heaviside function. The dynamics of \( G(t) \) (the global controller) is as follows:

\[
G(t) = \alpha H(z − \theta)
\]
\[ \frac{dz}{dt} = \sigma - \xi z \]  
(7)

\( \sigma \) is equal to 1 if the global activity of the network is greater than a predefined \( \zeta \) and is zero otherwise (Figure 6). \( \alpha \) and \( \xi \) are constants.\(^{15} \)

\( L_{i,j}(t) \) is the long range coupling as follows:

\[ L_{i,j}(t) = \begin{cases} 
0 & j \geq 30 \\
\sum_{k=225}^{256} w_{i,j,i,k}(t) H(x(i,k; t)) & j < 30
\end{cases} \]  
(8)

\( \kappa \) is a binary variable defined as follows:

\[ \kappa = \begin{cases} 
1 & \text{for CAM} \\
0 & \text{for CSM}
\end{cases} \]  
(9)

**Second Layer: Temporal Correlation and Multiplicative Synapses.** The second layer is an array of 256 neurones (one for each channel). Each neurone receives the weighted product of the outputs of the first layer neurones along the frequency axis of the CAM/CSM. For the CAM: Since the geometric (Euclidian) distance between rays (spectral maxima) is a function of the pitch of the dominant source in a given channel, the weighted sum of the outputs of the first layers along the frequency axis tells us about the origin of the signal present in that channel. For the CSM: Highly localized energy bursts will be enhanced by that representation.

Weights between layer one and layer two are defined as \( w_{H}(i) = \frac{\alpha}{7} \), where \( i \) can be related to the frequency bins of the STFT and \( \alpha \) is a constant for the CAM case, since we are looking for structured patterns. For the CSM, \( w_{H}(i) = \alpha \) is constant along the frequency bins as we are looking for energy bursts.\(^{16} \)

Therefore, the input stimulus to neurone \( (j) \) in the second layer is defined as follows:

\[ \theta(j; t) = \prod_{i} w_{H}(i) \Xi \{ x(i,j; t) \} \]  
(10)

The operator \( \Xi \) is defined as:

\[ \Xi \{ x(i,j; t) \} = \begin{cases} 
1 & \text{for } x(i,j; t) = 0 \\
x(i,j; t) & \text{elsewhere}
\end{cases} \]  
(11)

where \( \overline{()} \) is the averaging over a time window operator (the duration of the window is on the order of the discharge period). Multiplication is carried out only for non-zero outputs (in which spike is present)\(^{79,80} \). A functional analogue of this behavior has been observed in the integration of ITD (Interaural Time Difference) and ILD (Inter Level Difference) information in the barn owl’s auditory system\(^{79} \) or in the monkey’s posterior parietal lobe neurones that show receptive fields that can be explained by a multiplication of retinal and eye or head position signals\(^{81} \).

\(^{15} \zeta = 0.2, \alpha = -0.1, \xi = 0.4, \eta = 0.05 \) and \( \theta = 0.9 \).

\(^{16} \) In our simulation, \( \alpha = 1 \).
The synaptic weights inside the second layer are adjusted through the following rule:

$$w_{ij}'(t) = \frac{0.2}{e^{\mu|p(j;t) - p(k;t)|}}$$

(12)

$\mu$ is chosen to be equal to 2. The binding of these features is achieved via this second layer. In fact, the second layer is an array of fully connected neurones along with a global controller. The dynamics of the second layer is given by an equation similar to equation 5 (without long range coupling). The global controller desynchronizes the synchronized neurones for the first and second sources by emitting inhibitory activities whenever there is an activity (spikings) in the network [28].

The selection strategy at the output of the second layer is based on temporal correlation: neurones belonging to the same source synchronize (same spiking phase) and neurones belonging to other sources desynchronize (different spiking phase).

**Masking and Synthesis.** Time-reversed outputs of the *analysis* filterbank are passed through the *synthesis* filterbank giving birth to $z_i(t)$. Based on an output signal continuity criterion and on the phase synchronisation described in the previous section, a mask is generated by associating zeros and ones to different channels.

$$s(t) = \sum_{i=1}^{256} m_i(t)z_i(t)$$

(13)

where $s(N - t)$ is the recovered signal (N is the length of the signal in discrete mode), $z_i(t)$ is the synthesis filterbank output for channel $i$ and $m_i(t)$ is the mask value. Energy is normalised in order to have the same SPL for all frames. Note that two-source mixtures are considered throughout this article but the technique can be potentially used for more sources. In that case, for each time frame $n$, labeling of individual channels is equivalent to the use of multiple masks (one for each source).

**Experiments and Results.** Results can be heard and evaluated on one of the authors’ web page: [82] [83]. Detailed results and experiments are described in a companion paper by Pichevar and Rouat in the same book where a comparison is made to the work by Hu [72], Wang [28] and Jang [71].

Based on evidences regarding the dynamics of the efferent loops and on the richness of the representations observed in the Cochlear Nucleus, we propose a technique to explore the monophonic source separation problem using a multirepresentation bio-inspired pre-processing stage and a bio-inspired neural network that does not require any a priori knowledge of the signal.

Results obtained from signal synthesis are encouraging and we believe that spiking neural networks in combination with suitable signal representations have a strong potential for use in speech and audio processing. The evaluation scores show that the system yields performance levels roughly comparable with other
methods, to which it has been compared. Furthermore, our method does not need any prior knowledge and is not limited to harmonic signals.

5 Exploration in Speech Recognition

We illustrate here another application in speech recognition where perceptive signal analysis combined with non-linear signal processing and spiking neural networks offers a strong potential.

5.1 Auditory Based Features and Pattern Recognisers

Starting in the middle of the ’80s, many auditory models have been proposed [84,85], [86], [87,88], [89], [90,91], [92,93], [94] and have been tested on speech processing systems. At that time, it was objected that auditory models were CPU-intensive and were only useful when speech was noisy. Furthermore, that first generation of auditory-based models failed to be used by speech recognisers, since recognisers were not able to exploit the great granularity of auditory-inspired model outputs that preserve time structure and generate many simultaneous representations and features suitable to source separation and speech recognition. Furthermore, at that time, pattern recognisers were not able to exploit this information, as they were optimised for parameters (like MFCC) obtained through systematic analysis.

In pattern recognition research, it is well known that signal analysis and recognition are modules that are closely related. For example, very good matching between parameter vector (such as MFCC) distributions and recognition models (such as HMM) yields better performance than systems using auditory cues but with mismatched pattern recognisers. Further discussion is given by M. Hunt in [97,98].

Since then, research in neuroscience and auditory perception has advanced, yielding greater understanding of the auditory system along with more sophisticated tools for the recognition of time-organised features. See for example the work by Zotkin et al. [42].

5.2 Speech Recognition with Ensemble Interval Histograms

Oded Ghitza proposed in 1994 and 1995 the use of an auditory peripheral model for speech recognition [90,91] that simulates a great number of neurones with different internal threshold values. O. Ghitza introduced the notion of the Ensemble Interval Histograms representation (EIH). That representation carries information about the spiking time interval distributions from a population of primary auditory fibres. Experiments were made on the TIMIT database by using a mixture of Gaussian Hidden Markov Models. He observed that the EIH representation is more robust on distorted speech when compared to MFCC. On clean speech there was no gain in using that model.
It is important to note that EIH carries information on averaged spiking intervals, thus specific sequences of spikes can not be identified inside a population of neurones. Furthermore, the representation has to be smoothed to be compatible with the use of a conventional fixed frame pattern recogniser (HMM with multi-Gaussian). Therefore, fine grained information is lost. We suggest to use a similar front-end as proposed by Ghitza, but to preserve the time structure organisation of spiking sequences across neurones, without computing the histograms. As it prevents the conventional use of HMM, we examine potential techniques to recognise specific spiking sequences. Different coding schemes can be used to perform the recognition. In a collaborative work 17 the Rank Order Coding scheme is explored. The ROC scheme has been proposed for visual categorisation by Thorpe et al. 35,36.

The peripheral auditory system is crudely modelised and it is assumed that the auditory image representation can be processed as images. From preliminary experiments 99, it is observed that bio-inspired approaches could be a good complement to statistical speech recognisers as they might reach very quickly acceptable results on very limited training sets.

6 Conclusion

Conventional speech analysis and recognition techniques can yield good performance levels when correctly trained and when the test conditions match those of the training set. But for real-life situations, the designer has to train the system on huge databases that are very costly to implement. On the other hand, bio-inspired processing schemes can be unsupervised and generalise relatively well from limited data. They could efficiently complement conventional speech processing and recognition techniques. Due to the intrinsic spiking nature of neurones, suitable signal representations have to be found to adequately adapt the signal information to the neural networks.

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