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Formant Tracking Linear Prediction Model using HMMs for Noisy Speech Processing

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Abstract—This paper presents a formant-tracking linear prediction (FTLP) model for speech processing in noise. The main focus of this work is the detection of formant trajectory based on Hidden Markov Models (HMM), for improved formant estimation in noise. The approach proposed in this paper provides a systematic framework for modelling and utilization of a time- sequence of peaks which satisfies continuity constraints on parameter; the within peaks are modelled by the LP parameters. The formant tracking LP model estimation is composed of three stages: (1) a pre-cleaning multi-band spectral subtraction stage to reduce the effect of residue noise on formants (2) estimation stage where an initial estimate of the LP model of speech for each frame is obtained (3) a formant classification using probability models of formants and Viterbi-decoders. The evaluation results for the estimation of the formant tracking LP model tested in Gaussian white noise background, demonstrate that the proposed combination of the initial noise reduction stage with formant tracking and LPC variable order analysis, results in a significant reduction in errors and distortions. The performance was evaluated with noisy natual vowels extracted from international french and English vocabulary speech signals at SNR value of 10dB. In each case, the estimated formants are compared to reference formants.

Keywords—Formants Estimation, HMM, Multi Band Spectral Subtraction, Variable order LPC coding, White Gauusien Noise.

I. Introduction

FORMANTS , the resonant frequencies of the vocal track during voiced speech, are widely believed to be useful features which be exploited in various areas of automatic speech processing: speech recognition, speech synthesis, speaker identification[1]. . . Given the potential interest of formant data, an accurate formant model estimation is needed to deal with the problems of the variability of the number of formants across the phonemes and the merging and demerging of neighbouring formants (such as F2 and F3) over time. So, formant tracking is a difficult problem for which numerous works have been dedicated to design an automatic formant tracking algorithms. Formant trackers usually include two different phases: one in which the speech is analyzed and formant candidates are obtained, and another in which, by imposing different constraints, the most likely formants are chosen. While the first stage usually relies on standard spectrum estimation techniques: LPC estimation [2, 3], Cepstral estimation [4], the second stage has evolved notably in the recent years. Traditionally the second phase tries to impose continuity constraints on the formant selection process. Several approaches are used for the last stage, some include nonlinear smoothing operations which depend on good estimates in neighbour regions [5], either extends reliable formant estimates from "anchor frame" found in supposed strong vocalic areas [6, 7]. Both types of approaches are sensitive to wrong estimates and have a tendency of error-propagation. Another approach, which has gained in popularity, uses dynamic programming techniques [8, 9]; with the objective of minimizing the transition costs for all formant configurations possibilities, imposing continuity constraints between adjacent frames. This method usually find reasonable formant estimates when the formant trajectories are apparent, but can make gross errors even in vocalic regions, especially when formant candidates are occasionally missing [10]. The Hidden Markov Model approach to speech parameter trajectory estimation [11] offers another dimension of flexibility and tractability. HMM has provided excellent performance since it is build on the concept of global optimization, where the overall result is determined by the highest combined probabilities of a series of frames to occur in a given sequence. The approach presented in this paper introduces the notion of global optimization characteristic of HMMs and incorporate dynamic programming techniques for the Viterbi algorithm [13]. An important concept put forward is the computation of transition probabilities according to frequency and amplitude slope variations, rather than looking at the relative evolution of the trajectories directly on the frequency and amplitude axis. The accurate estimation or traking of formants embedded in background noise, is problem currently receiving considerable attention in the signal processing literature. However, due to noise in the speech signal, non- formant peaks can be confused for formant peaks and true formant peaks can be obscured. To account for this, many approaches were developed in the literature [14, 15, 16]. In Our research, the overall estimating formants' system was tested under an additives noise environment. So, and in order to tackle with this problem, we propose to incorporate a pre filtering stage designed around a multi-band spectral subtraction before estimating the formants by an algorithm based on variable order LPC Coding. Outline of this paper is as follow: in the next section, we present an overview of formant-traking variable order LP Model with HMM. In section 3, we present the details of the proposed algorithm of formants estimation in noisy environment based on a variable order LPC analysis with a system of pre-filtering noise designed around a multi-band spectral subtraction. In section 4, description of implemented Hidden Markov Model is introduced. Then, we

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present in section 5 the experimental results of the different techniques and give a critical performance evaluation of these methods. Finally, the conclusion of this work is stated.

II. AN OVERVIEW OF FORMANT-TRAKING LP MODEL WITH HMM

The block diagram describing different modules and their interrelation of the proposed Formant-Traking LP Model with HMM (FTLP-HMM) with de-noising speech is illustrated in Fig.1 and consists of the following sections: (1) A pre-cleaning module for de-noising speech incorporatin multi-bands Spectral Subtraction. (2) A formant LP model estimation incorporating variable order LPC analysis [17]. (3) A formant-tracking HMM model incorporating Viterbi trackers.

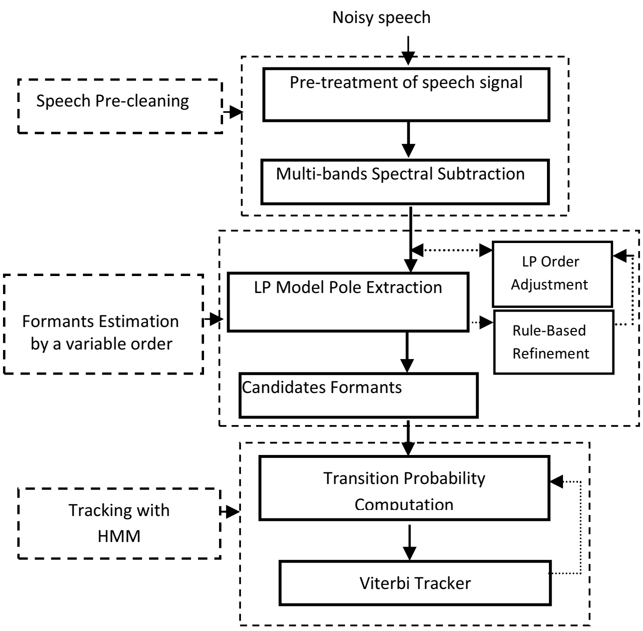

Fig. 1. Overview of the FTLP-HMM model for Formants Estimation of Noisy Speech.

III. FORMANTS ESTIMATION FROM NOISY SPEECH

In this section a robust formant LP model is introduced composed of pre-cleaning of speech spectrum followed by formant estimation.

A. Initial-Cleaning of Noisy Speech

After acquisition and pre-treatment, noisy speech spectrum is pre-cleaning with the multi-bands spectral subtraction method. The preceding methods assume an additive noise with constant spectral density such as white noise. To take into account the non-uniformity of the spectrum of other types of noise, Kamath [16] proposed a method, which involves cutting the spectre of noisy signal in interlaced N bands, and applying to each band a spectral subtraction.

B. Variable LP Order Rule Based Formant Estimation

There are several methods of formant extraction such as peak picking [3], HMM2 [18] and LP model pole extraction [2]. The main method used in this work is the LP model pole extraction combined with a rule based method for pole refinement. This method consists on estimating the formants directly from the poles of the vocal tract transfer function obtained by the LPC analysis [2, 3]. Indeed, each pair of conjugate poles represents a formant, but the problem is that there are pairs, which do not produce resonance. They are represented by the pairs of poles whose module is lower than 0.7 and the bandwidth is higher than 300 Hz [19]. The algorithm should suppress those poles and keep only the poles, which are conjugates with positive argument. Each formant Fi and its corresponding bandwidth BWi can then be calculated as follows [20]:

$$F_i = \frac{\theta_i}{2\pi T_i}, \quad BW_i = \frac{-ln(r_i)}{\pi T_i} \tag{1}$$

If the number of poles remaining after removal is insufficient to represent the number of formants requested, the segment will be analyzed again with a higher LPC analysis order (increment of the order). This process is repeated until obtain at least the requested number of formants. The poles obtained by the LPC analysis of the segment are sorted out so as to eliminate extreme poles. An extreme pole is a pole that does not engender any resonance (formant), which is a real pole, nil or its bandwidth exceed 300 Hz. It may happen that the number of obtained poles, after elimination, represents a number of formants upper than that asked. In this case, there will be discontinuity in the trajectory of formants. The solution to this problem is to measure the distance between the formant measured previously and the poles obtained, the pole with the lowest distance is the one who ensures the continuity of the above formant; we decided to hold her back. The decision criterion is based on the measure of Euclidean distance. If we assume that we must extract n formants, then the equations used to measure the Euclidean distance are:

$$d(F_i, C_k) = (\sum_{j=1}^{k}(c_j - f_j))^{\frac{1}{2}} \tag{2}$$

$$F_{i+1} = arg[min(d(F_i, C_k))] \tag{3}$$

C_k is the k^i formant obtained after the sorting and F_i is the i_i formant previously estimated. The initial condition for this recurring equation is the average estimated formants. The algorithm based on variable order LPC analysis, solves the problems of formants too close together or confused, missing formants (undetected) and the sensitivity of poles to the noise.

IV. HMM FORMANT TRACK ESTIMATION

Hidden Markov Model (HMMs) are quite powerful statistical models which are used to represent sequential data, the elements of HMM theory are described in a tutorial fashion [21]. There are three key problems associated with HMM theory [21].To apply HMM theory to the tracking problem we are primarily interested in the estimation problem, which is solved by the Viterbi algorithm [13]. In this section a description of implemented Hidden Markov Model is introduced, then state transition probability is computed, finally a design of the modified Viterbi algorithm proposed for formant estimation problem is presented.

A. Description of HMM for Tracking Problem

The major difference between HMM models usually encountered in standard literature and the model used in this implementation is the fact that the state transition probabilities evolve as a function of time, since they are obtained from the frequency and amplitudes of the formant candidates observed. In fact, the intuitive model of trajectory which was used is a time-sequence of peaks which satisfies continuity constraints on parameter slopes. Consequently, this method tends to identify trajectories whose amplitude and frequency slopes evolve smoothly in time. The type of HMM which was formalised by Garcia and Depalle [13] is described as follow, for each partial trajectory named frame we consider:

- n_t number of peaks at time t,
- $P_t[k]$,$0 \leq k \leq n_t$ order of frequency growing,
- $I_t[k]$, $0 \leq k \leq n_t$ index associate to each peak $P_t[k]$, When a peak $Pt[k]$ is detected as a spurious (i.e. $k > n_t$), it is associated with null index $I_t[k] = 0$.
- $F_t(k)$ frequency of the peak k of frame t,
- $A_t(k)$ amplitude of the peak k of frame t,
- S_t HMM state at time t defined by an ordered pair of vector (I_{t-1}, I_t)
- O observation defined by an ordered pair of integers (n_{t-1}, n_t).

Notice that only the combinatorial aspect was retained and that frequency and amplitude parameters of peaks are not taken as observations. In fact they are considered parameters of the Markov Model and are used to compute the transition probability between two states.

B. State transition probabilities computation

The state transition probabilities are obtained from the values of the frequency and amplitudes candidates for a given frame, using a criterion computation for apparied tracks and non-apparied ones. Garcia and Depalle in [13] evaluate a "matching criteria" $\theta_t(k)$ for each peak k of frame t, $0 < k < n_t$, this criteria depends on two other peaks i and j of frames t-2 and t-1 respectively, such that :

$$I_{t-2}(i) = I_{t-1}(j) = I_t(k) \tag{4}$$

This matching criterion is defined by equation (5) and (6) Where:

$$\Delta f_t(k,j) = a_t(k) - a_{t-1}(j), \Delta f_t(k,j) = f_t(k) - f_{t-1}(j)$$

And $\mu, \sigma_f, \sigma_a, \sigma_{fn}, \sigma_{an}$ are adjustable parameters of the computation. The idea is to compute a score which is high if the discontinuities in slope from frame candidates are low and these predictable frequency tracks are present in the state currently evaluated. The non-apparied criterion "death" is used to penalize the score of continuous slopes that are not identified as tracks in the current state evaluated. The procedure for the computation of the apparied criterion "birth", when indexes representing track numbers are non-zero is given by equation (5). The procedure for the computation of the non-apparied criterion, for state configurations with zero indexes (indicating the absence of trajectories) is similarly given in equation (6).

$$\theta_t(k) = \begin{cases} \text{if } I_t(k) > 0 \\ \exp\{-\frac{[\Delta f_t(k,j) - \Delta f_{t-1}(j,i)]^2}{\sigma_f^2} - \\ \qquad \frac{[\Delta a_t(k,j) - \Delta a_{t-1}(j,i)]^2}{a_t^2(j)\sigma_a^2}\} & (5) \\ \text{if } I_t(k) = 0 \\ \{1 - (1-\mu)\exp\{-\frac{[\Delta f_t(k,j) - \Delta f_{t-1}(j,i)]^2}{\sigma_{fn}^2}\}\} \times \\ \{1 - (1-\mu)\exp\{-\frac{[\Delta a_t(k,j) - \Delta a_{t-1}(j,i)]^2}{\sigma_{an}^2}\}\} & (6) \end{cases}$$

C. Modified Viterbi Algorithm

The approach taken for the design of a modified Viterbi sequence accepting the computation of transition probabilities according to frequency and amplitude slope variations and restricting formant trajectory crossings, births and deaths within a single window of frames. The Viterbi algorithm was used on a window of T frames length which slides frame by frame and we introduce some constraints on the index combinations. For instance, for given window "births" and "deaths" of peaks are disallowed to reduce the number of possible states, forcing the state sequences to have a constant number of trajectories. Consequently, there always exist two integers' i and j which satisfy the condition (4). Since there cannot be any births or deaths within a single window for which the optimal Viterbi sequence is calculated, the procedure is repeated while sliding the analysis window by one frame every time. The results of each window are stored and the births and deaths are determined by looking at all interpretation of a same frame transition. The modified algorithm output could be judged by comparing the results of sending the same transition probabilities for all frames to the original Viterbi sequence [22] results fed with only one copy of the same transition probabilities.

V. EXPERIMENTS AND RESULTS

This formant tracking algorithm was tested on several natural vowels extracted from international french and English vocabulary. For the algorithm prototype, Matlab [23] was chosen as the implementation language. This section reports on the results and is divided into three subsections. The first subsection focuses on a pre-cleaned linear predictive formants trajectory stage extraction. In the second subsection, focus on testing the impact of frame size parameters related to the HMM tracking algorithm. Finally, we give several illustrating on the performance of the proposed tracking algorithm in background white Gaussian noise with a signal-to noise ratio (SNR) of 10dB.

A. Pre-Cleaning Formants Candidates Generation

The natural vowels /aa/, /oee/ and /i/ are degraded by white Gaussien noise, extracted from NOISEX database [24], with an average SNR in the range of 10 dB. We use speech sampled at 44 kHz linearly quantized. We were interested in following the first three formants (F_1, F_2, F_3). The digital speech $s[n]$, where n is the sample index, is pre-emphasized with a pre-emphasis coefficient of 0.98, to partially compensate the spectral tilt of the speech signal. After pre-emphasis, the speech signal is windowed, using a 200 sample (25 ms) Hamming window every; 80 samples (10 ms) and 12th order LPC coefficients are computed for each window The algorithm based on variable order LPC coding presented in this paper is a modified and ameliorated version of the formants estimation algorithm by search for poles. Initially, the LPC analysis order is set at 12; the number of formants toextract is also fixed (number of formants asked). The poles obtained by the LPC analysis of the segment are sorted out so as to eliminate extreme poles. The poles of the LP model pre-cleaned using multi-bands spectral subtraction method applied for 8 bands. These poles are the formant candidates represented as formant trajectory.

B. Frame size Parameters Controls

Since formants are extracted, a HMM formant tracker is used to process the poles of the LP model and obtain an improved estimate of the LP model parameters. The first problem to handle in this step is fixing the size of frame parameters. In fact, as be shown in fig.2 controls related to the frame size are provided to get a good pre-liminary extraction, that the HMM algorithm will use to make clean tracks.

Fig.2 illustrates the performance of HMM tracking algorithm depending on the size frame. The frequency cells are marked along the vertical axis, and the time blocks marked along the horizontal axis The fig.2 (a) shows simulated of both the correct formant trajectories and the wrong one, which are interlaced, of the sequence of phonemes /Lalo/; when this trajectories are tracked with a small frame size, a major formant information is eliminated with the persist of the wrong ones as be shown in (b). A large frame size allows ridding the false formants even the correct one (c). Then by choosing the best size frame only the correct formants are saved (d).

C. Evaluation of Proposed Algorithm in Noisy Background

A qualitative assessment can be made with natural vowels by inspecting the coincidence of formants trajectories obtained by the algorithms tested with the spectrogram of the original signal presented in Fig.3, Fig.4 and Fig.5. For the purpose of evaluating the robustness of the proposed FTLP-HMM algorithm against environmental additive noise, we first studied the behavior of HMM tracking algorithm based on classic LPC analysis in the same test condition. The experimental results realized with three kinds of natural vowels aa, oee and i are illustrated by Fig.6, Fig.8 and Fig.10. These figures shown that both the high order and the low order trajectories of candidate formants of the noised phoneme could be affected: we notice the birth of false peaks between the formants trajectories (Fig.10) or the delete of candidates' peaks for each frame (Fig.6 and Fig.8). This first study proves the high sensitivity of the LPC coefficients to noise, the

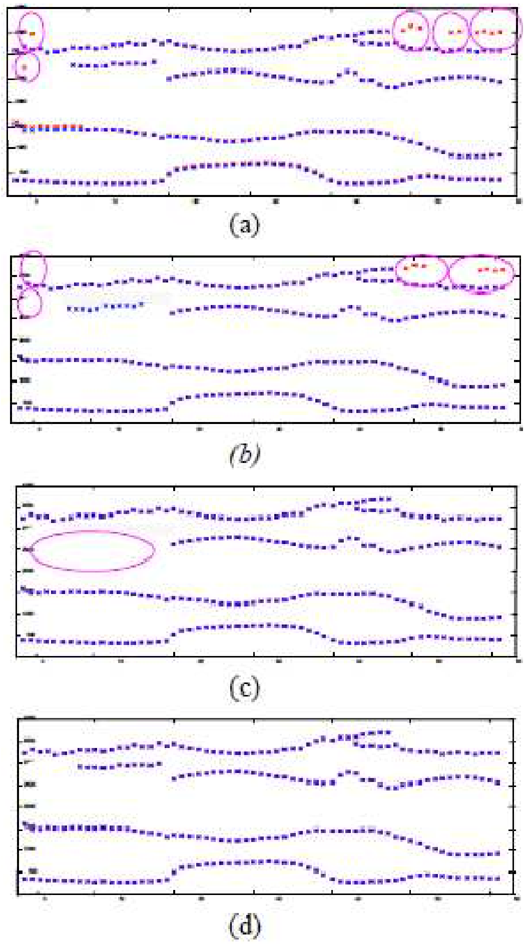

Fig. 2. Effect of the frame size in the Performance of HMM tracking algorithm: (a) the correct formants trajectory of the sequence of phonemes /Lalo/, (b) tracking with small frame, (c) tracking with large frame, (d) tracking with a best choice of frame.

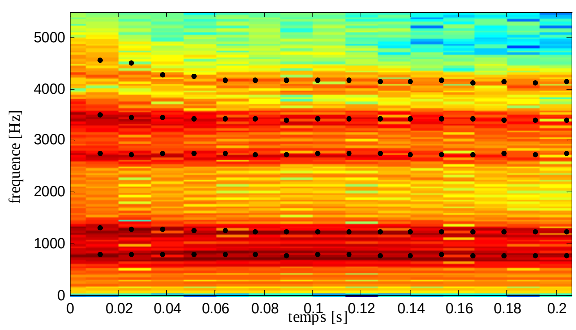

Fig. 3. Spectrogram and Formants trajectory of LPC poles model in clean environment for vowel /aa/.

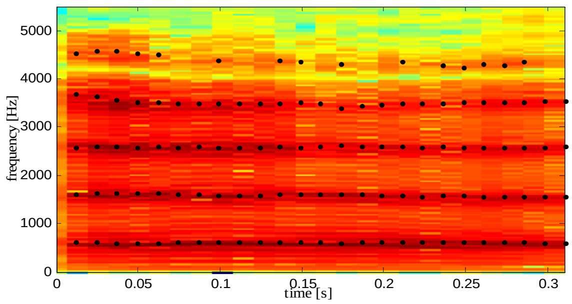

Fig. 4. Spectrogram and Formants trajectory of LPC poles model in clean environment for vowel /ooe/.

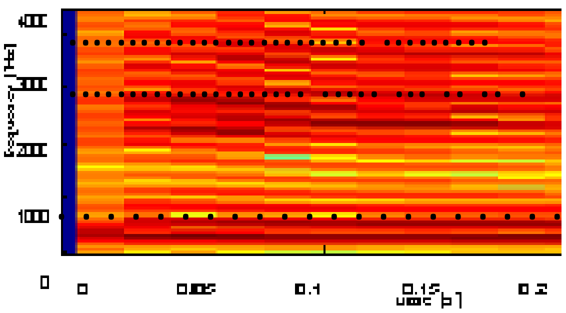

Fig. 5. Spectrogram and Formants trajectory of LPC poles model in clean environment for vowel /i/.

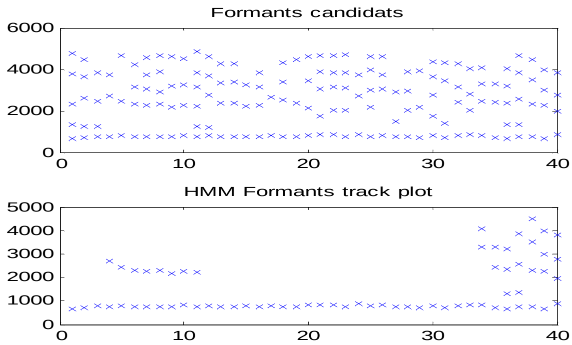

Fig. 6. Performance of HMM tracking with classic LPC for vowel /aa/ with SNR=10 dB.

LPC poles were affected considerably and their position and amplitude would be changed. This change causes erroneous formants frequencies by merging of neighbouring formants, or by creating a high discontinuity in formants trajectory. This discontinuity causes the division of trajectory in careers of short durations which make these latter considered as false trajectories by the tracking HMM algorithm and then they will be rejected. In order to remedy in the limitation of format track estimation based on LPC models under noisy condition, a second experiment was targeted on the same vowels; in this study the proposed FTLP-HMM algorithm was tested. Results presented by Fig.7, Fig.9 and Fig.11 achieve improvement of continuity in the most affected formant tracks.

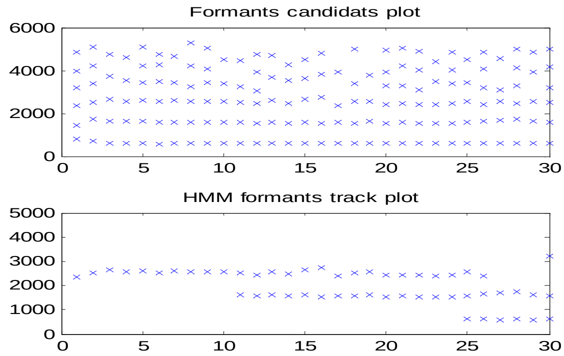

Fig. 7. Performance of HMM tracking with classic order LPC for vowel /ooe/ with SNR=10 dB.

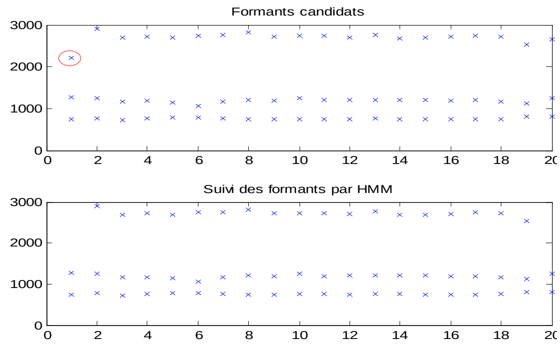

Fig. 8. Performance of HMM tracking with variable order LPC for vowel /aa/ with SNR=10 dB.

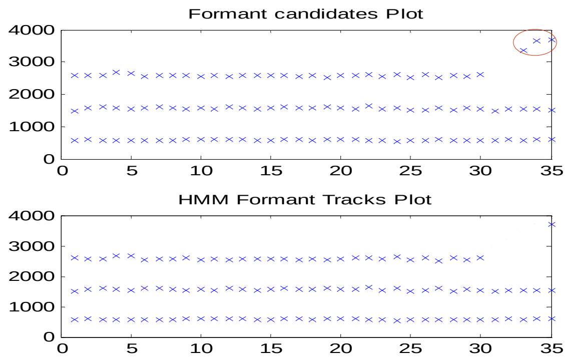

Fig. 9. Performance of HMM tracking with variable order LPC for vowel /ooe/ with SNR=10 dB.

The discontinuity of formants is assumed to be compensated by combination of variable order LPC analysis and de-noising block conceived around a multi-band spectral subtraction. So, these proposed techniques allow resolving the problems of the formants too closer or confused, the missing formants (not discovered) and the sensibility of poles to noise. Hence, improvement of continuity of formant tracks is mainly obtained by the best estimation of formants trajectory candidates which lead for a best HMM tracking. Trajectories of formants obtained by the algorithm are compared to the spectrogram

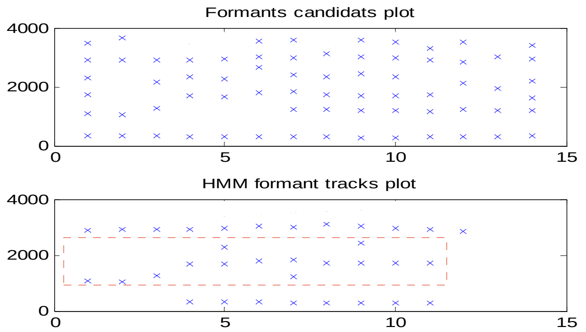

Fig. 10. Performance of HMM tracking with classic LPC for vowel /i/ with SNR=10 dB.

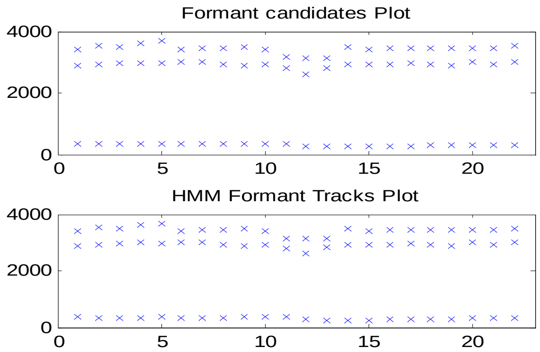

Fig. 11. Performance of HMM tracking with variable order LPC for vowel /i/ with SNR=10 dB.

of the original signal (without noise). We notice that formants trajectories coincide well with the dark areas representative of concentrations of energy the formants.

VI. Conclusion

This paper presents a novel algorithm for formant-tracking linear prediction (FTLP-HMM) model for speech processing in noise. The overall system was conceived around noise pre-filtering using a multi-band spectral subtraction, followed by a module for formants' estimation using a linear prediction technique 'LPC' operating with variable order. The formants trajectory generated are tracked using the probabilistic models Hidden Markov Model (HMM) with a Viterbi-decoder. This approach provides a systematic framework for modelling and utilization of a time- sequence of peaks which satisfies continuity constraints on parameter. This study proves the robustness of the proposed formant tracking method, evaluations of the de-noising block shows that it delivers improved results compared to algorithm based only on classic LPC method. In fact, the additions of the de-noising and variable order LPC analysis allow an efficient contribution to overcome the problems of speech formants trajectory tracking for noise effect. Since, they allow the compensation of the discontinuity of formants trajectories affected by noise which make their tracking by Viterbi-decoder more consistent for SNR level upper than 10dB. However, difficulty arises if background noise is lower than 10dB, we notice the trackers wander far away from the true formant values. Therefore, it may be necessary to incorporate a smoothing stage where Kalman filters are used to model the formant trajectories and reduce the effect of residue noise on formants.

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