SPEECH ENHANCEMENT USING PARTICLE FILTERS:A CRITICAL REVIEW

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Abstract:

Speech Enhancement refers to improvement in quality of a degraded speech signal in broad sense, however the aim is not only improvement of intelligibility but also overall quality, widely applied in de-reverberation, voice recognition systems, data matching in investigative fields and recovery of missing information i.e speech reconstruction. This paper presents a literature review of speech enhancement techniques, of all the methods available to us today ,we particularly concentrate on adaptive filtering method, due to successive implementation of Kalman filter in recent years and current research that has been carried on over particle filter this paper reviews the comparisons of the two. It has been observed that particle filters outperforms Kalman filters when it comes to non-linear ,non Gaussian noise removal.though the limitation is number of particle in particle filter.

Keywords:- Particle Filter, Speech Enhancement, RBPF,STSA-RBPF, Neural Network

1.INTRODUCTION

Enhancement of any kind refers to improving the quality of the object. In case of speech processing is improving the quality and intelligibility of deteriorated or corrupt speech signal [1],[7],[10]. Speech Enhancement not only deals with noise reduction[2-7] but also removal of echoes and separation of independent signals, also the problem of separating convolutively mixed signals[13] such as cross talk multi channel is considered under enhancement, Also recovery of lost part of speech data [5],[7].

Quality of speech is subjective measure refers to pleasantness or naturalness of sound, whereas Intelligibility is an objective measure predicts percentage of words that can be correctly identified by the listener. The various ways in which speech is enhanced is broadly classified as:-

(1).Spectral Subtraction

(2).Subspace Methods

(3) Adaptive Filtering

(4). Model Based Enhancement

(5).Minimum Mean Square Estimators (MMSE)

(6).Frame Based Processing

(7).Super Gaussian Estimates

(8).Harmonic and Impulsive Noise

(9).Missing Feature Extraction

(10).Bandwidth Expansion

(11).Reverberation

Of all the methods available to us we particularly concentrate on Adaptive Filtering Method being one of the most significant and widely used enhancement technique as it yield better noise suppression results without considerable distortion in speech signals , also phase recovery can be done which was a major drawback of spectral subtraction. The methods such as sub space analysis and spectral subtraction are somewhat outdated technologies those were outperformed by adaptive filtering a long ago,there are a variety of adaptive filters available to us today including LMS filter ,RLS filter,Weiner Filter and most significant work in last years has been done over Kalman filters and its variants which was due to its ease of implementation [5][6],better results and flexibility of algorithms[8][3][1] , Classical methods to obtain approximations tothe desired distributions include analytical approximations, such as the extended Kalman filter the Gaussian sum filter , and deterministic numerical integration techniques . The extended Kalman filter and Gaussian sum filter are computationally cheap, but fail in difficult circumstances [13],Such as its lack of performance in non linear ,non Gaussian domain .Particle filter is a popular topic of research in this area that overcomes these difficulties, now a days ,hence we have here reviwed Particle Filter and its combination with other algorithms and models and had dicussed the various aspects.[1]-[13]

1.1 PARTICLE FILTER

Recent years have witnessed tremendous interest in nonlinear filtering techniques in general and particle filters in particular[1]-[8]. Particle filters or Sequential Monte Carlo (SMC) methods are a set of on-line posterior density estimation algorithms that estimate the posterior density of the state-space by directly implementing the Bayesian recursion equations. SMC methods use a grid-based approach, and use a set of particles to represent the posterior density. These filtering methods make no restrictive assumption about the dynamics of the state-space or the density function. SMC methods provide a well-established methodology for generating samples from the required distribution without requiring assumptions about the state-space model or the state distributions. The state-space model can be non-linear and the initial state and noise distributions can take any form required. However, these methods do not perform well when applied to high-dimensional systems. SMC methods implement the Bayesian recursion equations directly by using an ensemble based approach. The samples from the distribution are represented by a set of particles; each particle has a weight assigned to it that represents the probability of that particle being sampled from the probability density function[12]. The figure below represent a basic particle filter algorithm.

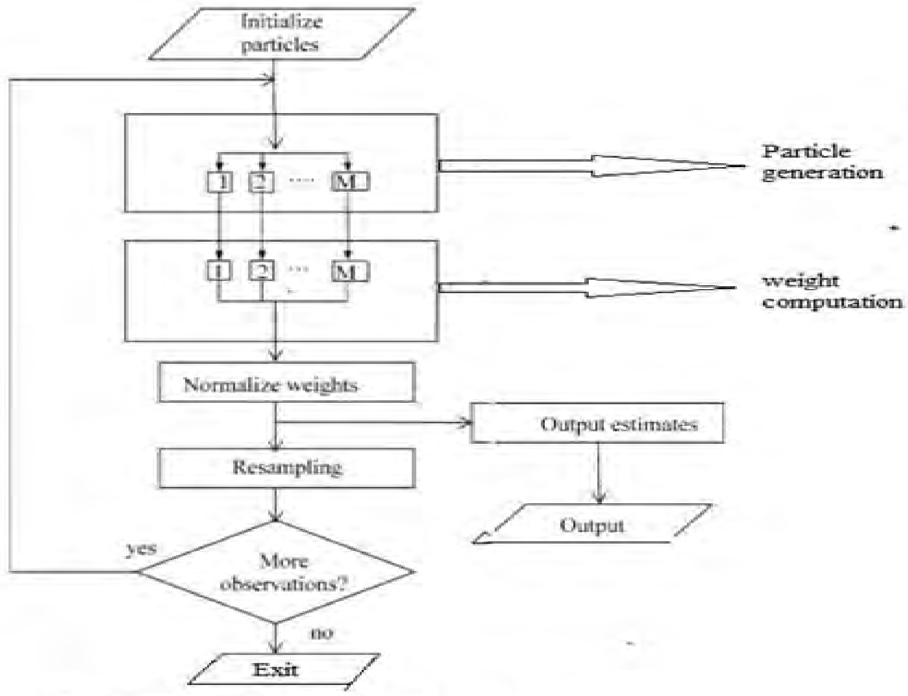

Fig:1 Basic particle filter algorithm [1]

Weight disparity leading to weight collapse is a common issue encountered in these filtering algorithms; however it can be mitigated by including a re-sampling step before the weights become too uneven. In the re-sampling step, the particles with negligible weights are replaced by new particles in the proximity of the particles with higher weights.

Many algorithms have been reported in literature[1]-[8], and some are available in the form of pseudo code or even real source code. However, there does not seem to be a unified software package that contains major algorithms and options and is readily available. Though particle filtering approach is very efficient method for non linear non gaussain noises,its performance for Gaussian noise are compared with iterative kalman filters and other adaptive filters too[4].Paper [6] represents the basic particle filtering approach generally known as Monte-Carlo method ,which mentions that particle filter is a flexible approach that can be applied to non linear and non Gaussian models where kalman filter are suboptimal and unreliable.

Particle filter use discrete random sample representations of probability distributions obtained through Monte Carlo simulation to perform recursive Bayesian estimation of state of a system described by a general space model

$$X_n = f_n(x_{n-1},d_n)$$
$$Z_n= g_n(x_n,u_n)$$

Where x_n is the state,z_n is the measurement and the equations above are state-space transition and measurement equations.The system measurement noises d_n and v_n are assumes to be independent of x_n ;however ,unlike kalman filtering they need not to be Gaussian distributed. Xn denotes the true state vector at time n while $x_n^{(i)}$ denotes the ith candidate state vector,also called a aprticle .the notation p(.) is used to denote a probability density function ,for example $x_n^{(i)} \sim p(x_n)$ indicates that the particles are distributed according to pdf of true state ,in particle filtering densities are approximated by set of samples $\{\mathbf{x}_n^{(i)}\}_{i=1}^{N_P}$,in the state sspace ,and their associated $\{W_n^{(i)}\}_{i=1}^{N_P}$ as

$$p(\mathbf{x}_n|\mathbf{z}_{1:n}) \approx \sum_{i=1}^{N_P} W_n^{(i)} \delta\left(\mathbf{x}_n - \mathbf{x}_n^{(i)}\right) .$$

2 PERFORMANCE ANALYSIS

2.1 Neural Network based Particle Filter [1][4]

Particle filters are combined with neural networks presents a solution to computational cost constraint of particle filter by minimizing no. of particles required by preprocessing the speech[1][4].Paper [4] presents the comparison between various non linear Particle Filter algorithms approach with dual-non dual, multiple neuron-single one,bias-non bias conditions.the result is enlisted in the table.

TABLE I

AVERAGE RESULTS FOR COMPUTER-GENERATED COLORED NOISE. EACH SCORE IN THE TABLE IS AGAIN OBTAINED BY AVERAGING THE INDIVIDUAL SCORE FROM 120 SIMULATIONS (20 SIMULATIONS FOR EACH OF SIX TEST SENTENCES). WITHIN EACH COLUMN, BOLD CHARACTERS ARE USED TO HIGHLIGHT THE TWO BEST SCORES. FOR EXAMPLE, AT A SCALE OF 0.02, THE TWO BEST SEGMENTAL SNRS ARE 5.74 AND 5.69

Type of algorithm	*Quality measure*	Scale 0.04	0.03	0.02	0.01
Noisy speech	SNR	-2.35	-1.12	0.92	4.68
	wPESQ	1.16	1.24	1.40	1.83
NPF-$\bar{d}$-$\bar{m}$-$\bar{b}$	SNR	2.90	4.07	5.65	8.63
	wPESQ	**1.68**	1.93	2.27	3.06
NPF-$\bar{d}$-$\bar{m}$-b	SNR	2.34	3.69	5.48	8.55
	wPESQ	1.61	1.88	2.24	3.02
NPF-$\bar{d}$-m-$\bar{b}$	SNR	**3.00**	**4.11**	**5.74**	**8.72**
	wPESQ	**1.69**	**1.97**	**2.31**	**3.09**
NPF-$\bar{d}$-m-b	SNR	2.41	3.74	5.55	8.60
	wPESQ	1.65	**1.94**	2.28	3.08
NPF-d-$\bar{m}$-$\bar{b}$	SNR	2.25	3.52	5.24	8.30
	wPESQ	1.48	1.60	1.93	2.69
NPF-d-$\bar{m}$-b	SNR	1.85	3.14	4.90	8.02
	wPESQ	1.42	1.54	1.88	2.66
NPF-d-m-$\bar{b}$	SNR	2.42	3.65	5.36	8.49
	wPESQ	1.52	1.70	2.13	2.80
NPF-d-m-b	SNR	2.12	3.27	5.19	8.32
	wPESQ	1.51	1.70	2.10	2.75
RBPFLin	SNR	**3.09**	**4.18**	**5.69**	**8.67**
	wPESQ	1.63	1.90	**2.34**	**3.18**

[4]

2.2 Rao-Blackweillized Particle Filter [2][4][5][7]

RBPF is a very popular choice of particle filter variants as seen in[2][4][6][7],The paper [2] compares filter using single channel filtering algoritms,filtering algorithms of particle filter with its last hierarchal pre-decessor kalman filter,kalman filter had been a very prominent topic of research in previous years but [5] shows that kalman algorithm methods fails at high SNR when particle filter performs well,paper [2] shows the PSEQ index of kalman v/s variant of particle filter.

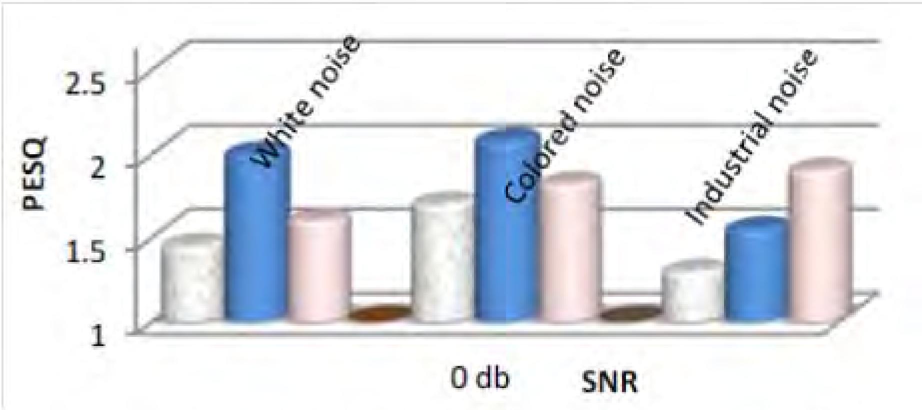

Fig 2 : SNR vs PSEQ score of kalman vs particle [2]

The graph from [2] shows the PSEQ scores for different kind of noises where noisy speech (grey),RBPF(blue) ,IKF(pink) are compared,As can be clearly seen from the graph above Particle filter yields a high optimal result for white and coloured noise and marginally outperformed in industrial noise by iterative Kalman filter by a naarow margin

Statistical analysis of Kalman v/s RBPF filter [5]

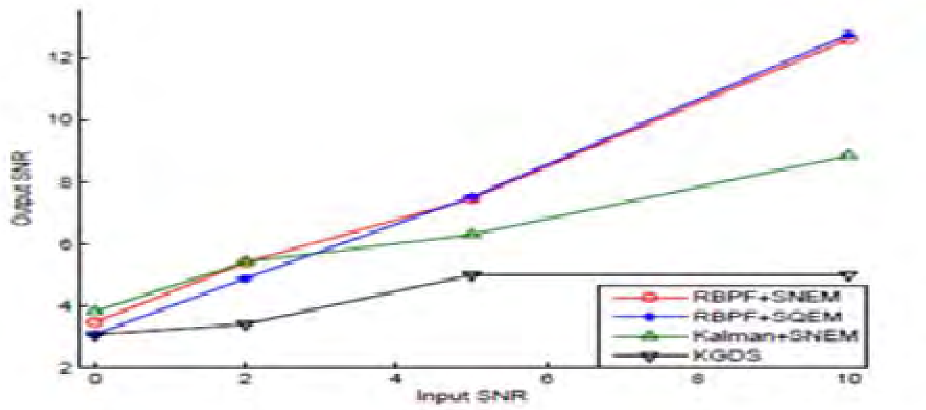

Fig 3 Seqential speech enhancement performance analysis [5]

The graph above shows us the margins by which the signal to noise ratio of Kalman variants differ with particle filters also that particle filter results are even satble for higher SNR scenario where Kalman seems to fail

2.3 Sub Band Particle Filtering [7]

Moreover paper[7] presents the idea of subband particle filtering and its performance comparison with its fullband version. through experiments that the subband domain particle filter performs better in terms of segmental SNR as compared to the corresponding fullband domain algorithm

TABLE II

Comparison of SegSNR improvement in colored noise.

Input SegSNR(dB)	SegSNR improvement(dB)			
	Cohen [33]		Subband PF	
	Traffic	F-16	Traffic	F-16
-5	7.64	5.98	7.82	8.12
0	5.67	4.07	5.30	6.77
5	3.30	2.59	3.14	4.75
10	1.23	0.83	1.11	2.89

[7]

The table shows the various changes observed in SNR when speech is segmented , paper[7] alsoconsiders the result over Gaussian white noise also with better results of sub band.

2.4 Short Time Spectral Amplitude Particle Filter [3]

The generic particle filter algorithm can be combined with models such as listed in [3].The table below presents the comparative analysis of version of particle filter models and kalman filter.Paper [3]shows particle filtered modeled as Short Time Spectral Amplitude Particle Filter (STSA-PF) and Interacting Multiple Model STSA (IMM-STSA-PF).STSA Phase.Objective analysis result of multiple models enlisted in the table below[3].

TABLE III

OBJECTIVE EVALUATION SCORES FOR STREET NOISE

	WPESQ Score			CSII Score		
	0 dB	10 dB	20 dB	0 dB	10 dB	20 dB
Noisy	1.07	1.41	2.15	0.21	0.76	0.97
RBPF	1.10	1.49	2.21	0.22	0.75	0.97
DCT-RBPF	1.24	1.73	2.45	0.40	0.84	0.96
STSA-PF	1.27	1.81	3.05	0.45	0.89	0.98
STSA-fAR	1.28	1.81	3.06	0.46	0.89	0.98
STSA-dAR	1.27	1.81	3.06	0.46	0.89	0.98
STSA-IMM	1.28	1.84	3.11	0.47	0.89	0.98
STSA-Phase	1.30	1.82	2.97	0.48	0.88	0.97

[3]

The above table shows relative CSII and WPSEQ scores for various PF variants with short time spectral amplitude considerations and best scores obtained were 1.84 WPESQ and .89 CSII for 10dB scale consideration.

The graph below from [3]compares the particle filter variants runtime requirements:-

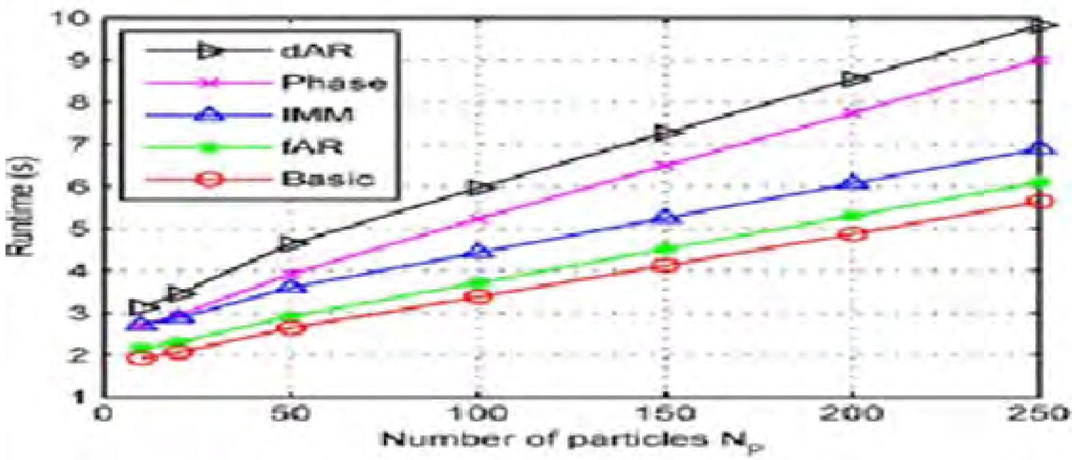

Fig 4 Runtime comparison for particle filter variants (processing 2 seconds of speech sampled at 16 khz [3]

We have already compared particle filter on various speech based criteria the graph above shows the runtime requirements for particle filter as we increase no of particles for various algorithms which suggests phase estimation would require greater time as we move toward precision.

Lastly here the comparison of particles in a particle filter in [6] gives us by the tables below

TABLE IV

Particles number	10	100	250	400	500	900	1000	1500
output $SNR(dB)$ voiced sequence	5.2	6.5	8.1	11.2	12.3	15.6	25.1	25.1
output $SNR(dB)$ unvoiced sequence	5.7	7.9	13.2	19.7	26.4	29.8	30.3	30.3

Variation of the output SNR versus the number of particles (input $SNR = 5\ dB$)[6]

TABLE V

Particles number	10	100	250	400	500	800	1000	1500
output $SNR\ (dB)$ voiced sequence	5.1	5.9	7.7	10.1	11.9	14.7	22.1	22.1
output $SNR\ (dB)$ unvoiced sequence	5.5	6.9	12.8	18.9	24.4	27.8	28.2	28.2

Variation of the output SNR versus the number of particles (input $SNR = 10\ dB$) [6]

the three significant results drawn are :-

- the performance of the particle filter are as better as the particles number is large,
- no significant decreasing of the errors is performed when N is greater than 1000,
- the performance of the particle filter are better for the $SNR = 5\ dB$ than for the $SNR = 10\ dB$

3.COMPARISON :-

The table below compares the recent existing Particle Filter algorithms and variants with Kalman filter variants over various aspects such as MSE,PSNR,WPESQ score,CSII scores over various kind of noises commonly encountered in Speech.

TABLE VI- Comparison between various particle filter algorithms

S.No..	Reference Paper	Algorithm Used	Measurement Parameter	Advantage	Disadvantage
1.	[1][4]	Neural Network Based Particle Filter	MSE (0.0011) PSNR (77.7687)	Decreases computational cost by reducing no of particles by presprocessing speech	If we remove the part of signal resembling noise ,we are bound to remove parts of speech signal that resembles noise
2.	[2][4][5][7]	Rao Blackwellised Particle filter	SNR, (8.68 dB at 5 dB input)[4][5] PESQ(Perceptual Evaluation Speech Quality) (2.68 at .015 scale)[4]	RBPF works well even when SNR is high	Computational cost of RBPF is high
3.	[3]	-Short Spectral Amplitude Particle Filter(STSA-PF) -Interacing Multiple Model STSA PF(IMM-STSA-PF) -STSA-Phase	-Wideband Perceptual Evaluation Speech Quality(WPESQ-Score)(1.90 for WGN) -Coherence Speech Intelligibility Index(CSII Score) (0.72 for WGN)	STSA-PF variants outperforms iterative kalman filter	The performance is better when no. of particles increased
4.	[4]	Neural network+ RBPF	SNR (5.67 and 5.79 at .02 Scale) ,WPESQ (2.31 and 2.34 at same scale)	Neural particle filter with dual, multiple neuron ,no bias conditions gives best results in case of coloured,white,real world noises	It is beneficial to employ several neurons even though it drastically increase the amount of computation per iteration.
5.	[5]	Variants of RBPF,Kalman Filter	SNR At i/p =5dB (KDGS-4.5 dB RBPF+SQEM-8dB)	Kalman gradient method fails at high SNR where RBPF performs well	Performance of RBPF depends on no of particles, increasing them increases cost of the system
6.	[6][8]	Particle Filtering	SNR , NMSE (Normalized Mean Square Error) (For N>1000 25.1Db for voiced and 30.33 for unvoiced)	Flexible Method can be easily applied to non-linear ,non Gaussian models where kalman methods are suboptimal	Performance of particle filter is better at High SNR
7.	[7]	Sub band particle Filter using RBPF	SNR Full band-3.42 Subband-9.61 (at 5dB)	Performs better in terms of segment SNR	Paper assumes noises are stationary

As can be seen from the table above the reason why particle filter has been considered over Kalman is quite clear High SNR i.e 5.67 and 5.79 with higher WPSEQ score of 2.31 and a mean square error so small we can visualise particle filter as a replacement of Kalman specially for non linear application.

4. CONCLUSION AND FUTURE SCOPE :-

This critical review paper concludes that gaining advantages over all existing adaptive filtering methods Particle filter in speech enhancement can yield better results not only in terms of SNR and reduced MSE ,in linear as well as non linear domain ,with no such restriction of noise being Gaussian, it also outperforms existing algorithms in case of higher SNR case, not only flexibility of particle filter is considerable, but also ease of implementation, although increase in number of particle leads to precision but also increases computational costs where as limiting particle over range 1000 gives a handshaking solution.

The Particle filter and its combination with other algorithms can be used as efficient voice recognition tool combined with other filters, also speech enhancement methods can use particle filteres as feedback or cascade structures for better results.

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