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Embolic Doppler Ultrasound Signal Detection via Fractional Fourier Transform

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Abstract—**Computerized analysis of Doppler ultrasound signals can aid early detection of asymptomatic circulating emboli. For analysis, physicians use informative features extracted from Doppler ultrasound signals. Time –frequency analysis methods are useful tools to exploit the transient like signals such as Embolic signals. Detection of discriminative features would be the first step toward automated analysis of embolic Doppler ultrasound signals. The most problematic part of setting up emboli detection system is to differentiate embolic signals from confusing similar wave-like patterns such as Doppler speckle and artifacts caused by tissue movement, probe tapping, speaking etc. In this study, discrete version of fractional Fourier transform is presented as a solution in the detection of emboli in digitized Doppler ultrasound signals. An accurate set of parameters are extracted using short time Fourier transform and fractional Fourier transform and the results are compared to reveal detection quality. Experimental results prove the efficiency of fractional Fourier transform in which discriminative features becomes more evident.**

I. Introduction

In computer aided diagnosis systems, final diagnostic decisions are made with the aid of automated signal and image analysis methods. A reliable computerized analysis of embolic signals (ES) can aid early detection of asymptomatic circulating emboli. Deep venous thrombosis caused from blood clot is usually seen in legs. Moreover, arterial thromboembolism caused from atherosclerosis is seen in arterials of heart, neck, and brain. Thromboembolism is dangerous and has to be detected in meantime in order to get an early treatment. Doppler ultrasound has a wide range of usage in thromboembolism detection in medicine [1].

The main logic behind Doppler ultrasound systems depends on the signals of blood flow velocity in arteries. Basically, embolic Doppler ultrasound signals are transient signals that occur in a short interval. In order to improve the accuracy the ES detection, an appropriate signal processing method must be incorporated to increase the ratio of the ES to the background blood signal.

Embolic signals have some distinctive characteristics. Because emboli is much bigger than red blood cells, intensity of the Doppler signal reflected by emboli is much higher than the signals obtained from normal blood flow, which are termed as Doppler speckle (DS). DS has also a random wave-like pattern in the intensity of Doppler signals while ES has regular oscillating, wave-like patterns. In addition to that, ES have narrower bandwidth in comparison with DS in general. There are also artifacts which are caused by tissue movement, probe tapping, speaking etc. in Doppler ultrasound signals [2].

Doppler ultrasound detection systems are based on quadrature demodulation resulting in quadrature signal having in-phase and quadrature-phase components. The first step in detection ES is to convert the quadrature signal into forward and reverse components [3]. This will help to better differentiate ES from artifact, as ES is unidirectional [2].

In literature, detection of embolic signals using Doppler ultrasound has been studied with various techniques. An audio-visual feature detection compared with human experts has been studied in [4]. In another work, spectral characteristics of embolic signals have been searched [5]. A neural network approach for real time identification has been introduced in [6]. Time-Frequency (TF) analysis and processing of arterial Doppler signals have been proposed to detect high-intensity transient signals in [7]. Various types of TF analysis methods were compared for peripheral embolus detection in [8]. Matching pursuit method which is based on TF analysis for detection of emboli has been studied [9]. A rule based expert system for automated embolus identification has been introduced in [10]. A power m-mode Doppler is used for observing cerebral blood flow and tracking embolic cases in [11]. Basic signal processing methods, such as Fourier and wavelet transforms have been exploited for deeper analysis in [12] and [13].

In this work, main goal is to find discriminative features to detect embolic Doppler ultrasound signals using fractional Fourier transform (FrFT) and compare with the results obtained by short time Fourier transform (STFT), which is extensively used in Doppler ultrasound systems. In the next section of this study, a brief introduction and main idea of FrFT is given. Experimental results are discussed in Section III and then conclusion is given in Section IV with summarized results.

II. Fractional Fourier Transform

Fourier transform (FT) is widely used in many scientific and engineering applications. Briefly, the FT extracts the spectral content of the signal $x(t)$, (FT{ $x(t)$}$\rightarrow X(f)$). But the main disadvantage of FT is the lack of localization of time-varying changes in a signal. If the localization is important as in non-stationary signals, TF transforms presents a good approach for inspection of time and frequency information together. However, the relationship between time and frequency resolutions is reciprocal.

FrFT is firstly introduced by Namias [14]. Relatively a

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long time later, this idea has attracted many scientists and researchers from various disciplines [15]. Fundamentally, FrFT is generalization of the ordinary FT and can be considered a TF analysis method used in signal processing, pattern recognition etc. The a^{th} order FrFT (F^a) of any signal $f(x)$ can be shown as

$$F^{a}\{(f(x))\} \equiv \int_{-\infty}^{\infty} K_{a}(x,x')f(x')dx' \qquad (1)$$

where $K_a(x,x')$ is the kernel function and the parameter a is termed as 'order of transform' and defined for $0 \le a \le 4$ as in [16-17] or can be defined $0 \le a \le |2|$ as in [18].

$$K_{a}(x,x') \equiv A_{\alpha} \exp[i\pi(x^{2}\cot\alpha - 2xx'\csc\alpha + x'^{2}\cot\alpha)]$$

$$A_{\alpha} \equiv \frac{\exp(i\pi\,\mathrm{sgn}(\sin\alpha)/4 + i\alpha/2)}{|\sin\alpha|^{1/2}} \qquad (2)$$

where the parameter α is called as transformation angle and defined as

$$\alpha = a\frac{\pi}{2} \qquad (3)$$

It can be considered that the ordinary FT is a special case of FrFT which directs us to a brief defination: 'ath order FrFT is the ath power of FT operator'. However, it must be noted that 'a' need not to be an integer [19]. So, FrFT can transform any signal to an imaginary intermediate domain that can be placed between time and frequency axes. According to the degree of FrFT operator, relationship with signal operations can be summarized as follows [20]:

- The zeroth or fourth order of FrFT corresponds to signal itself (when a=0 or a=4). In this case kernel becomes $K_{0\_or\_4}(x, x')\equiv\delta(x-x')$ as an identity operator on signal.
- The first order of FrFT is equals to the FT operator (when a=1) when the kernel approaches ordinary FT kernel $K_1(x, x')\equiv\exp(ix\,x')$.
- The second order of FrFT corresponds to reversed version of the signal (when a=2). In this case kernel becomes $K_2(x, x')\equiv\delta(x+x')$ as a reflection operator on signal.
- The third order of FrFT is equals to the inverse FT operator (when a=3) when the kernel approaches ordinary inverse FT kernel $K_3(x, x')\equiv\exp(-ix\,x')$.

The discrete versions of FrFT (DFrFT) are obtained by different types of techniques. There is not an exact definition that fully provides the requirements of DFrFT. For this reason, different approaches were developed for approximation to continuous FrFT while sacrificing some of the properties. In this work, we also use discrete version of continuous form. Main headlines of different approaches for DFrFT can be given as in [21]:

a. Direct form of DFrFT,
b. Improved sampling-type DFrFT
c. Linear combination-type DFrFT
d. Eigenvector decomposition-type DFrFT
e. Group theory-type DFrFT
f. Impulse train-type DFrFT
g. Closed form of DFrFT

III. EXPERIMENTAL RESULTS

A. Explanation of Dataset

Database used in the experiments is exactly the same database that is used in [2]. It consists of three types of Doppler signals: Embolic Doppler signals (ES), Doppler speckles (DS) and signals with artifacts. The signals in this study were recorded by a commercially available transcranial Doppler system (EME Pioneer TC4040) with a 2-MHz transducer. According to this database, recordings were made from the ipsilateral middle cerebral artery of 35 patients with symptomatic carotid stenosis. ES were identified subjectively by two experienced observers from both the FFT spectral display and the audio signal using conventional criteria [22]. Hilbert transform was applied as a preprocessing step to the quadrature audio Doppler signals containing ES as in [2]. It must be noted that ES are placed in the first halves of the signals on purpose. In this way, second halves of the signals only contain background components of signals.

Totally 25 recordings have been extracted from the original database in order to evaluate and compare the obtained results with previous findings. Each of the signals in the database is 2048 sample length with the sampling frequency of 7150Hz. A clear example of ES is shown in Fig.1a. Here, it is obvious that after 70 ms from the beginning of signal, there is a high risk of emboli. Nevertheless, not all the signals are clear and easily extractable like the one in Fig.1a.

B. Proposed Detection Approach and Results

Main goal in this study is to prove the efficiency of DFrFT on the detection of embolic signals. Hence, STFT is chosen for appropriate comparing of the final results. In every step similar approaches has been applied for STFT as well as DFrFT. In this study, eigenvector decomposition type of DFrFT is used throughout the experiments. All the signals in database are normalized as a part of preprocessing step. After normalization step, DFrFT and STFT transform methods are used. After this point, detection framework can be divided into two main phases briefly:

a. Generating smoothed versions of DFrFT and STFT outputs with a spline based curve fitting technique which helps also suppressing unwanted peaks produced by transform methods.
b. Discriminative parameters are obtained using smoothed coefficients after curve fitting process for the detection of ES.

In essence, FrFT needs an optimum a value as shown in (3) to reveal hidden time-frequency characteristics. Some examples for different a values are shown in Fig.1b-e. It is clear that the most distinctive and meaningful results (having peak at embolic pattern interval) have been gathered for the value of a = 0.09.

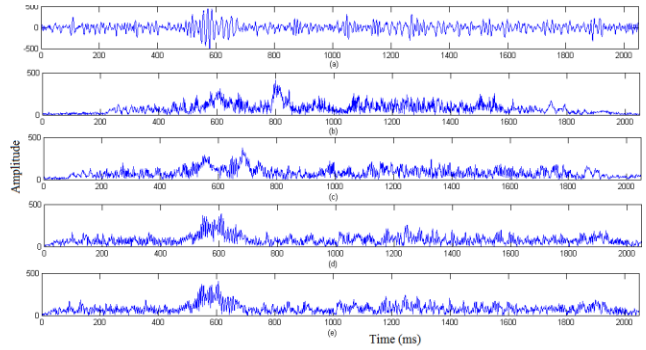

Figure 1. Example of FrFT outputs of the input signal for different a values: (a) sample input signal, (b) a=0.5, (c) a=0.3, (d) a=0.1, (e) a=0.09

To define *a* value firmly, all of the signals in database are evaluated by a set of *a* values. In the final results at empirical trials, *a* value is set to 0.09. In order to find STFT coefficients, spectrogram of the input signal is computed by applying Gaussian window with the length of 128.

DFrFT and STFT give discrete output values with ripples and noise-like small values. For this reason, a smoothing step is applied to clean unwanted effects of transform outputs. Moreover, smoothing step also helps exposing the peak values; hence more meaningful results are obtained. The largest peak value of the smoothed signal gives ES location, but there are other peak values that may mislead the system. A smoother and curved output signal, where ES has largest peak value and artifacts suppressed, is needed. After smoothing step, a spline based curve fitting method is incorporated using first *n* largest peak values with suppressed background. *n* was chosen to be 8. So, we can focus on the most discriminative parts of the signal and get rid of local maxima. The normalized fitted curves for DFrFT and STFT are shown in Fig.2b and Fig.2c respectively.

To find discriminative features, parameters have been extracted in a similar way as used in [2]. Those parameters are also important for the detection and classification task of ES. In the definitions of parameters, one of the most important steps is the threshold selection. In this study two types of threshold are considered:

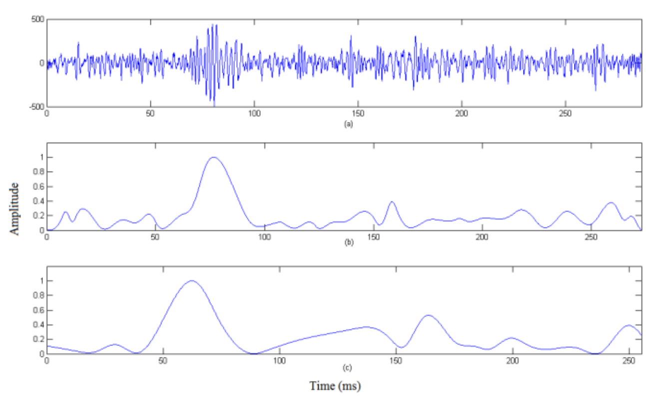

Figure 2. Normalized fitted curves for DFrFT(b) and STFT(c) outputs of input signal.

- Average value of the total signal (A_{tht}) is the mean of the total curve fitted signal.
- Average value of the background signal (A_{thb}) is the mean of the curve fitted signal without first part of the signal which contains ES signal.

Besides, the peak value of ES is names as A_{pk} which is another parameter of interest seen in Fig.3.

t_{on} and t_{off} values are the representing the beginning and the end of ES in Fig.3. t_{pk} is the time value of the ES where it reaches its peak.

With these threshold formations following ratios are defined and explained briefly:

Peak to Background Threshold Ratio (*EBR*): This is the ratio between the peak value and the mean value of background. It is expected for this value to be high for successful extractions.

$$EBR = 10\log(A_{pk} / A_{thb}) \tag{4}$$

Peak to Threshold Ratio (*P2TR*): This is the ratio between the peak value and the mean value of the transformed signal. It is calculated as:

$$P2TR = 10\log(A_{pk} / A_{tht}) \tag{5}$$

Total Power to Threshold Ratio (*TP2TRall*): This is the ratio between the integral value of the signal during the potential start and the end points (t_{on} and t_{off}) and A_{tht}.

$$TP2TRall = 10\log\left(\sum_{k=t_{on}}^{t_{off}} A(k) \Big/ A_{tht}\right) \tag{6}$$

Total Power to Background Threshold Ratio (*TP2TRbkg*): This is the ratio between the integral value of the output signal during the potential start and the end points (t_{on} and t_{off}) and A_{thb}.

$$TP2TRbkg = 10\log\left(\sum_{k=t_{on}}^{t_{off}} A(k) \Big/ A_{thb}\right) \tag{7}$$

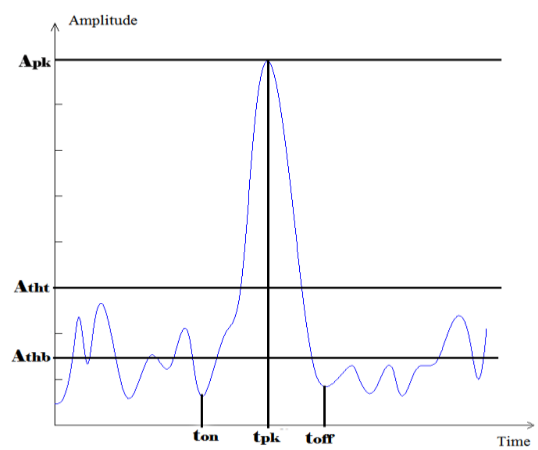

Figure 3. Parameters used for calculating the threshold ratios.

ES Rise Rate (*RR*): This is the ratio between P2TR and integral value of the output signal during $t_{on} - t_{pk}$.

$$RR = P2TR / (t_{pk} - t_{on}) \tag{8}$$

ES Fall Rate (*FR*): This is the ratio between P2TR and integral value of the output signal during $t_{pk} - t_{off}$.

$$FR = P2TR \,/\, (t_{off} - t_{pk}) \quad (9)$$

The mean and standard deviation results of 25 recordings are shown in Table I.

TABLE I. COMPARISION TABLE FOR STFT AND FRFT WITH MEAN AND STANDART DEVIATION RESULTS

Parameters	*STFT*		*DFrFT*	
	Mean	*Std*	*Mean*	*Std*
EBR	13.493	4.163	20.743	4.336
P2TR	11.049	2.809	17.482	2.976
TP2TRall	63.894	3.587	48.715	6.069
TP2TRbkg	66.338	4.957	51.159	7.067
RR	0.074	0.030	0.178	0.060
FR	-0.066	0.022	-0.180	0.085

The EBR parameter of DFrFT output is greater than STFT output, hence it can be said that DFrFT increases ES conspicuity, as also shown in from Fig. 2. Moreover, it can be noticed that the STFT output enlarges ES interval while DFrFT output keeps width of ES localization in reasonable borders. The P2TR parameter has also a larger peak value when a total threshold is used as can be seen from Table1. Same comments can be made as in EBR parameter for DFrFT.

Fig.2 shows that the STFT output spreads out the ES duration comparing to the DFrFT output. Because of this, total power of STFT output is larger than DFrFT while threshold values do not vary at all. This makes TP2Trall and TP2TRbkg for STFT output give larger values than DFrFT output. It is clear that one of the biggest advantages of DFrFT is to keep the ES interval support as it has in original.

Absolute values of the RR and FR parameters are expected to be larger in a robust system. The DFrFT helps fast steeping ES output in an acceptable way and increase success rate of detection comparing to STFT.

IV. CONCLUSION

In this study, DFrFT for characterizing ES, DS and artifacts is proposed. It has been shown that the discriminative features generated by DFrFT help easier analysis and detection of ES. Results show that proposed method reveals ES more apparently, and suppresses DS and artifacts. As a result of this feature of DFrFT, EBR and P2TR parameters are improved as compared with STFT which is a standard TF method used in Doppler ultrasound systems. Other parameters used in this study also emphasize the efficiency of DFrFT as a signal processing tool.

In Doppler ultrasound signals there is a certain degree of overlap between statistical properties of ES and DS. For this reason, it is challenging task to differentiate ES from DS. To conclude with, this study proves that improvement of detection and classification system can be accomplished using parameters obtained by DFrFT method.

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