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Shape Preserving Fitting Model for Affective Curves Extraction: An Affective Computing Method on fMRI Dataset

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Abstract

New breakthroughs were taken from the research of affective curve extracting from sequence-concentrated functional Magnetic Resonance Imaging (fMRI) images, and the emotional responses of human brain were hidden in these fMRI dataset; the purpose of this paper is to acquire critical features from fMRI images. The fMRI experiments were given by a certain theme emotion stimuli; firstly, component operations under bilateral filtering were applied for fMRI images' morphological segmenting which reduced the computational space, for that the calculation was not based on the whole brain space. Operated by Fast Fourier Transform (FFT), fMRI images relative to functional area of human brain were pre-processed. Finally, time series based Power Spectrum Density (PSD) was founded by using an improved shape preserving fitting algorithm, and affective curves were acquired subsequently. The results showed the effectiveness of the proposed methodologies in this paper by comparing with cubic fitting and 5-th polynomial fitting operations. Experimental results also showed that this method was effective and efficient; the shaper preserving model had the lowest residual error that reflected the brain's emotional response curve adequately. The proposed methods have potential applications in the study of human-machine emotion interactions.

Keywords: *fMRI; Fast Fourier Transform; Power Spectrum Density; Affective Computing; Shape Preserve Fitting*

1. Introduction

Affective computing (AC), a hotspot in artificial intelligence (AI) research, is an interdisciplinary field spanning computer sciences, psychology, and cognitive science. To date, affective computing research mainly focuses on the physiological signal acquisition, such as surface electromyography (sEMG) or dynamic electromyography (dEMG) [1, 2], which is a method for evaluating and recording the skeletal muscles' electrical activity and it is performed an electromyography continue to produce an electromyogram that detects the electrical potential generated by muscle cells, the signals can be analyzed for detecting medical abnormalities, activation level, or analyzing the emotions of human brain. Further researches were appeared in surface electrocardiogram recorded signals (sECG) [3]. But sEMG, dEMG, and sECG technologies had some deviations on detection and modeling, such as electronic signal is more simplicity produced by skin that is an uncertain model between skin and brain. And the second method is Electroencephalography (EEG) which measures voltage fluctuations resulting from ionic current flows within the neurons of the brain. EEG measured potential means of further experiments to get the variation of brain waves [4] and to extract the brain wave characteristics associated the emotional changes of human

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brain [5]. Of which there is a significant problem in the affection changes associated with how to reflect the theme affection discrimination? Dimensional emotion model was addressed to resolve this problem, such as, 2-dimensional emotion model [6], which proved that emotion constrained two factors: pressure (happy/sad) and energy (calm/excited); furthermore, it was divided into four categories: satisfaction (Contentment), depression (Depression), abundant (Exuberance) and sadness/frenzy (Anxious). Hevner [7] also introduced theme emotion recognition model and applied it in music-emotion research, and demonstrated that emotions were experienced in the music and not necessarily refer to the emotions experienced by the listener. The basic foundations of dimensional emotion were considered for emotion calculation under weakening-conditions. Representing the emotion by using words or affective words will lead to an possibility way to find the change of human brain and it was also reduce the calculation complexity, on the other hand, we also can enrich the content that words related to extend the emotional word performance in practices; researchers from Carnegie Mellon University observed the changes in cerebral blood flow of the human body in a particular emotional word stimulus through fMRI (functional magnetic resonance imaging). Results showed that the theme emotional words and the brain specific physiological feelings region were high correlation, such as, prefrontal cortex and the amygdale, which brought a very feasible direction for researching affection change of human brain by fMRI [8]. fMRI procedures to measure brain activity by detecting associated changes in blood flow. To date, Blood Oxygen Level Dependent (BOLD) fMRI was the most widely used method for mapping neural activity in the brain [9, 10] , there also had amount of previous researches through combining signals from many brain regions to predict the subject's behavior during a scanning session of fMRI[11, 12].

But affective words for different people have different subjective experience and such differences will affect the stability of the cerebral part of the changes in the characteristics. For this important issue, Affective Norms for English Word (ANEW) was developed for the major categories of emotional stimuli, such as happy, sad, calm, and the anger of the four major categories of a number of topics to reflect this broad category emotional picture sets, which is fixed by the large-scale applied in IPAS system [13], the stable stimulus through the photo album, and the commonality of human emotions, can overcome such weaknesses.

However, processing methods in fMRI studies were difficult; especially looking for an effective mathematical tool to express the fMRI presentations and the algorithms for the emotional reasoning mechanism. The synthesis mechanisms also had some problems. Among many of those tools, fuzzy set was considered to be an effective tool, which was introduced by L.A. Zadeh in 1965, it was different from the classic set collection system and used a membership function to react the degree of reaction thing belongs, fuzzy inference system was applied in affective computing [14]and medical fields [15]. In the fMRI data preprocessing, principal component analysis (ICA) [16], Fourier transform [17], and spectrum calculation [18], are very common methods. Results for image segmentation means of computer image processing, such as Gaussian filtering, it also included some De-noising practices. For fMRI timing image set, timing approach would be applied, such as hidden Markov chain model [19]. In addition, the timing set based feature-extraction after pre-processing of fMRI, fuzzy clustering methods, and rule-based fuzzy inference system played an important role in the calculation of fMRI.

Using spectrum calculation and fuzzy reasoning techniques to study the fMRI was the important content to reflect the diagram sequencer of human brain; and the timing spectrum scatter plot which was fetched from the fMRI images dataset will be fitted by curve, such as shaped preserving fitting model proposed in this paper. After manipulations on emotional words related curves. Final result in composite emotion synthesis will be acquired, and by comparing with other fitting means, such as polynomial fitting (3 orders and 5 orders), the results show the strong robustness of the proposed method in this paper. This paper presents pre-processing methods and fitting algorithms for the emotional words combined into complex emotional which provided a feasible method for fMRI dataset based affective computing. The proposed method in this paper has potential value in the customer evaluation of human-computer interaction applications. The framework of this paper was illustrated by Figure 1.

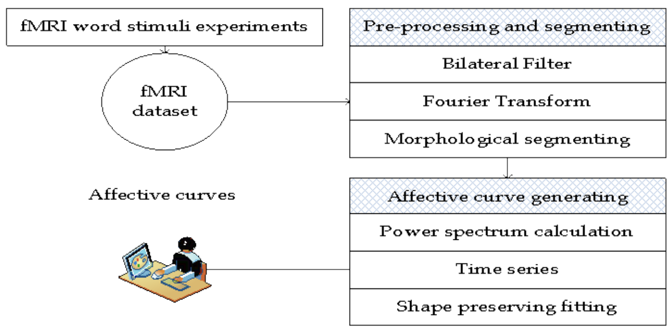


Figure 1. The Framework of Fuzzy Bayesian Inference on Composite Emotion Synthesis by using Shape Preserving Fitting Model to fMRI Dataset

2. Preliminaries and Methods

2.1. Preprocessing De-noising and Segmenting on fMRI Images

Noisy reduction is the process of removing noise from a signal. All recording devices have traits which make them susceptible to noise, and in this paper, bilateral filter was applied for fMRI images' nosy reduction. Bilateral filter (BF) is an edge de-noising filter methods that is constituted by two functions, one is to calculate the filter coefficients through a given geometric distance and another is depended on pixel difference. BF has obvious fuzzy edge effect instead of Gaussian filter. Let

$$B(X) = k_d^{-1} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} f(\eta) c(\eta - X) d\eta \tag{1}$$

be a transform on fMRI images, and for preserve the DC, let k_d be:

$$k_d = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} c(\eta) d\eta \tag{2}$$

, then the range filtering was calculated by

$$k_r^{-1}(X) \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} f(\eta) S(f(\eta) - f(X)) d\eta \tag{3}$$

Photometric pixel similarity was defined as

$$k_r(X)=\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}S(f(\eta)-f(X))d\eta \tag{4}$$

But it is resulted that range filter need to be combined with domain to enforce both geometric and photometric locality that will be defined by

$$k_r^{-1}\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}f(\eta)c(\eta-X)S(f(\eta)-f(X))d\eta \tag{5}$$

and by

$$k_r(X)=\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}c(\eta-X)S(f(\eta)-f(X))d\eta \tag{6}$$

for normalizing. The BF was combined Gaussian distribution in this paper, for bilateral Gaussian filtering, let

$$c\left(\eta-X\right)=e^{-\frac{1}{2}\left(\frac{d(\eta-X)}{\sigma_d}\right)^2} \tag{7}$$

, where $d\left(\eta-X\right)=\left\|\eta-X\right\|$ is a Euclidean distance, and the similarity function is calculated by:

$$Sim(\eta-X)=e^{-\frac{1}{2}\left(\frac{\delta(f(\eta)-f(X))}{\sigma_r}\right)^2} \tag{8}$$

, where $\delta(f(\eta)-f(X))=\left|f(\eta)-f(X)\right|$ is a norm in intensity space. In this paper, fMRI images were filtered by bilateral Gaussian model. And Fourier transform is a traditional mathematical method in many applications which defined a mathematical function of time as a function of frequency as frequency spectrum. This transform has the follow formula,

$$F(x(\varpi))=\hat{X}(\varpi)=\frac{1}{L}\int_0^L X(t)e^{-i\varpi t}dt \tag{9}$$

But in fact, in fMRI imaging processing, sample inputs as discrete under limited or finite duration was required; as one of discrete transform, Discrete Fourier Transform (DFT) was applied in computer science and image process. Given N points $\{X_n \mid n=0,1,\cdots N\}$, $DFT(X)$ is defined as:

$$\hat{X}_k=\sum_{n=0}^{N-1}e^{\frac{-2nk\pi i}{N}}X_n \tag{10}$$

, where $k=0,1,\cdots,N-1$. And its inverse is that

$$X_n=\frac{1}{N}\sum_{k=0}^{N-1}e^{\frac{2nk\pi i}{N}}\hat{X}_k \tag{11}$$

Fast Fourier Transform (FFT) is an improvement of DFT that is a way to compute under the same result but more quickly and have $o(n \log n)$ operations. FFT has widespread applications in fMRI images' in spatial frequency domain [20] and magnitude spectrum analysis [21].

For fMRI image based extraction research, full brain fMRI dataset is not required but focused on some functional related image zones that will be require image segmenting operation, so we need to retrieval certain volex set; and for each fMRI images, segmenting by using morphological methods is necessary[22]. Morphological method on fMRI image processing will conduct a binary image that morphological perimeter is 1 or 0, which the morphological perimeter is directly adjacent fore-color pixels to the background. 8-conections was used for all eight pixels surrounding a given pixel as adjacent (shown in Figure 2)

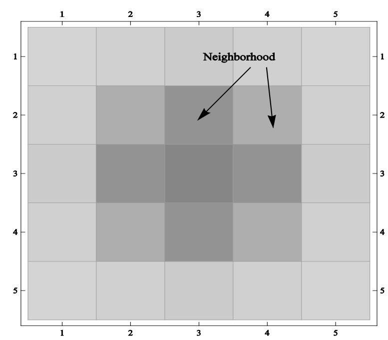


Figure 2. 8-Neighborhoods for Image Filter

And the calculating matrix is defined by:

$$T = \begin{bmatrix} 1 & 1 & 1 \\ 1 & -8 & 1 \\ 1 & 1 & 1 \end{bmatrix} \tag{12}$$

2.2. Time Series Foundation of fMRI Power Spectrum Density

The power spectral density (PSD) was adopted in this paper, which describes how the power of a time series based fMRI image is distributed with frequency instead of energy spectral density (ESD), which also describes how the energy of a time series is distributed with frequency [23]. Started from ESD, under a finite total energy; mathematically, supposed that time series based fMRI image is described by a square integrable function. Proved that signal after FFT operation was satisfied this condition. ESD was defines as:

$$E(\varpi) = \frac{1}{2\pi}[\int_{-\infty}^{\infty} g(t)e^{-i\varpi t}dt]^2 = \frac{1}{2\pi}F(\varpi)F^*(\varpi) \tag{13}$$

, where $\varpi = 2\pi f$, f is ordinary frequency, $F^*(\varpi)$ is complex conjugate of $F(\varpi)$. And for discrete time series based fMRI signal, we have:

$$E(\varpi)=\frac{dt^2}{2\pi}[\sum_{n=-\infty}^{\infty} g_n e^{-i\varpi n}]^2=\frac{dt^2}{2\pi}F_d(\varpi)F_d^*(\varpi) \tag{14}$$

, where $F_d(\varpi)$ is the discrete-time Fourier transform of g_n. Power spectral density, for abstracting time series based fMRI signals more exactly; PSD can be defined as the squared value of the signal. Let $P(t)$ be $g(t)\times g(t)$, then by Fourier transform we have that,

$$PSD(\varpi)=\lim_{T\to\infty} \quad E([\frac{1}{T}\int_0^T g(t)e^{-i\varpi t}dt]^2) \tag{15}$$

For a given magnitude scale $[A_1, A_2]$, frequency band need to be applied for calculating by

$$PSD=\int_{\varpi_1}^{\varpi_2}(PSD(\varpi)+PSD(-\varpi))d\varpi \tag{16}$$

And for discrete $T=ndt$, continuously, we have that,

$$PSD(\varpi)=\frac{dt^2}{T}[\sum_{n=1}^{N} g_n(t)e^{-i\varpi n}]^2 \tag{17}$$

2.3. Shape Preserving Fitting

For given time series dataset, (x_i, y_i), $i=0,1,\cdots,n$, $x_0<x_1<\cdots<x_n$, consider a function $f:[x_0,x_n]\to R$ satisfying $f(x_i)=y_i$, $i=0,1,\cdots n$. And there also have monotonicity, convexity, smoothness, approximation order, locality, and fairness issues, which will be deducted to complexity mathematical calculations. Normally, tension methods were a revised cubic interpolation, we have that:

$$f(t)=\frac{a+bt+ct^2+dt^3}{1+\lambda_i t(1-t)} \tag{18}$$

, where $t=\dfrac{x-x_i}{x_{i+1}-x_i}$.

For $\lambda_i>-1$, $i=0,1,\cdots n-1$, f can be determined as the solution of a strictly diagonally dominate tridiagonal linear system[24]. In some special cases of monotone, we can select

$$\lambda_i=\mu_i+(f'(x_i)+f'(x_{i+1})\frac{x_{i+1}-x_i}{y_{i+1}-y_i} \tag{19}$$

, where $\mu_i\ge -3, i=0,1,\cdots,n-1$.

Cubic operating on each interval $[t_i, t_{i+1}]$ and

$$r''(t_i^+)=r''(t_i^-)+v_i r'(t_i) \tag{20}$$

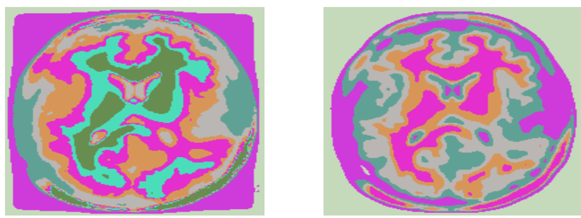
We have that,

$$r(t)=\frac{a(1-s)^3}{w_i s+1}+b(1-s)+cs+\frac{ds^3}{w_i(1-s)+1} \tag{21}$$

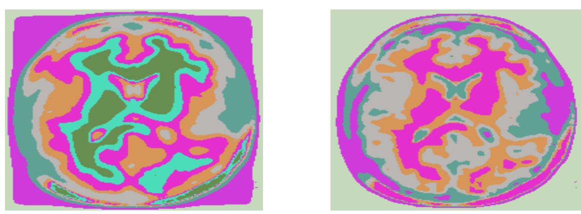
, where $s=\dfrac{1-t_i}{t_{i+1}-t}$ and $w_i \geq 0$ are the tension parameters [25].

3. Results and Discussion

The first step is to get clustering components operations under bilateral filter of fMRI dataset, let α be spatial spread, β be the pixel value spread, γ be the number of components. The results were shown in Figure 3.



(1) $[\alpha=5, \beta=0.3, \gamma=8]$ (2) $[\alpha=3, \beta=0.5, \gamma=6]$

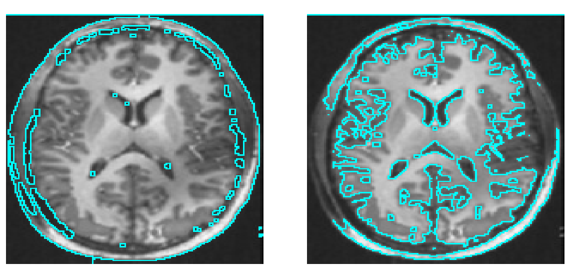


(3) $[\alpha=5, \beta=0.5, \gamma=8]$ (4) $[\alpha=3, \beta=0.3, \gamma=6]$

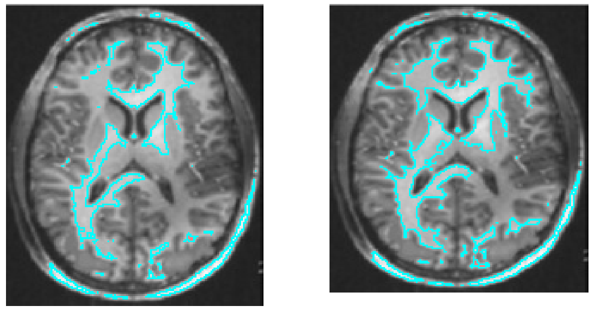
Figure 3. Components under Bilateral Filtering on fMRI Images with Different Spatial Spread, Pixel Value Spread and Components

The filter process of fMRI is a necessary step for segmenting; given different foreground scale and number of segments, we got fMRI segmenting results by using morphological method proposed in Section 2.1 (shown in Figure 4); and the valence-arousal related segments were located and extracted.

Let (a,b) be the fore-threshold and segment, we have that,



(a,b)=(0.21,2) (a,b)=(0.42, 4)



(a,b)=(0.67, 8) (a,b)=(0.72, 10)

Figure 4. Segmenting of Brain's fMRI by Different Foreground Scale and Number of Segments by Morphological Method

We located the block on one of 8 segmenting felids, and calculated the relative power spectrum density that proposed in Section 2.2 shown as Figure 5.

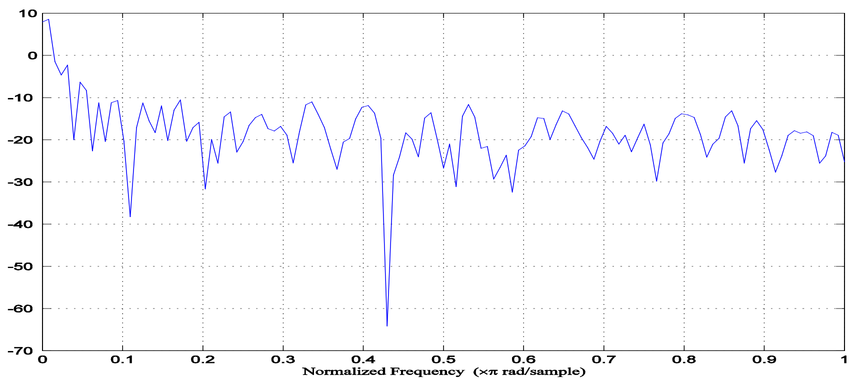


Figure 5. Power Spectrum Density of a Certain Segment of fMRI Image

Using formula (17), we can get result for total t-interval and from each fMRI images; we can create time series scatter point shown in Figure 6.

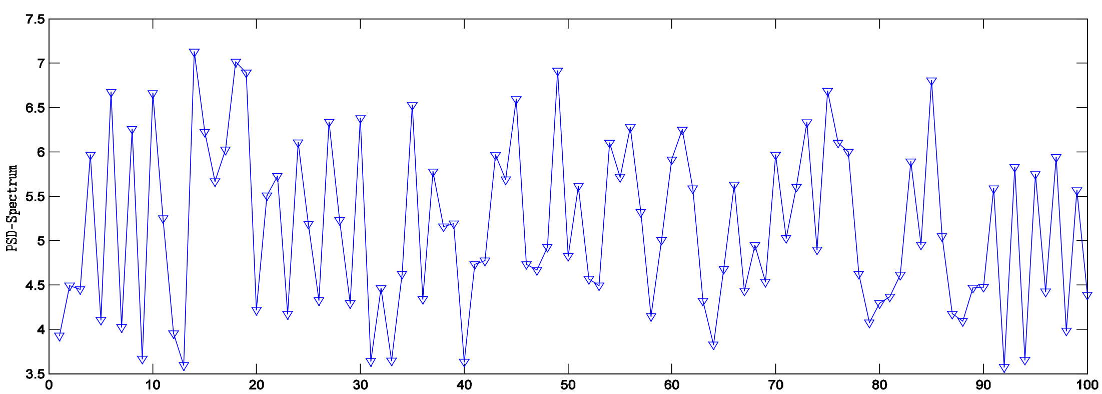


Figure 6. Time Series PSD Scatter Pot (100 points) from the Same Segment of fMRI Images

Figure 6 showed the results that PSD calculating from fMRI time series based images that will reflect the trend of affective response of human brain. And the next step is to select a fitting curve and described this trend. We adopted shape preserving fitting model and cubic, 5^{th} polynomial fitting operating by comparing analysis, the residents show that shape fitting is 0, and cubic is 9.39, 5^{th} polynomial fitting is 9.17. Figure 7 illustrated the fitting results and their residuals in Figure 8.

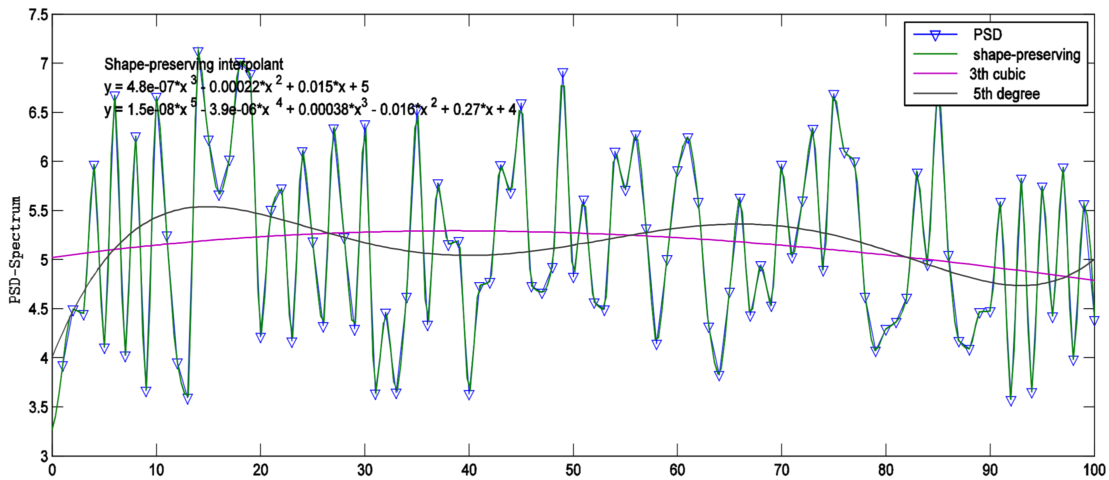


Figure 7. Time Series PSD of fMRI Images under Shape Preserving, Cubic, and 5^{th} Polynomial Fitting Model

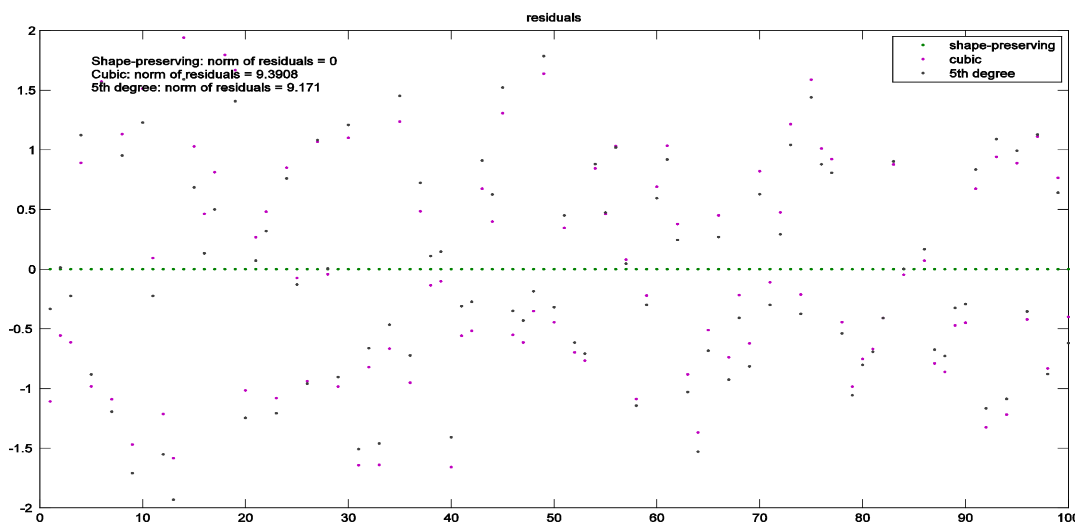


Figure 8. Residuals for Shape Preserving, Cubic, and 5^{th} Polynomial Fitting Respectively

The results showed that shape preserving fitting model had minimal residual. Hence, it was an effectiveness method for extracting affective curve from fMRI images by using shape preserving fitting. And affective curves exacted from different zones or functional areas of human brain were consisted of human emotion space, through the curves manipulations, complexity emotion curve will be constructed in further research.

4. Conclusions and Future Works

Extracting hidden emotional information from fMRI images is currently the most effective and powerful way to explore the functional areas of human brain's activities; to date, fMRI has its most accuracy and completeness on information acquiring for human brain research. In this paper, timing PSD feature-line extraction technology will bring new research direction on fMRI images' processing. Through a comparative study, the proposed method in this paper was regarded as an effective method. Although, fMRI dataset pre-processing methods are vary, such as Gaussian filter and Laplace segmenting, the bilateral filtering and morphological segmentation proposed in this paper also are feasible for pre-processing on fMRI dataset. Shape preserving fitting model has minimal information loss by comparing with cubic and 5th polynomial fitting. Therefore, the conclusions of this paper are as follows:

(1) Bilateral filtering and morphological segmenting for fMRI preprocessing reduced the calculation complexity.

(2) Shape preserving fitting was regarded as an effectiveness method under minimal residuals by comparing with cubic and 5^{th} polynomial fitting for affective curve exacting.

The future work is to look for different segmenting algorithms and determine the difference between these algorithms, and second is to reduce the order of shape preserving fitting model under more weakness conditions.

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