The outstanding performance of the device is attributed to the use of high bandgap InGaP as the Schottky layer so as to improve the noise figure and reduce the gate leakage current, along with the use of AlGaAs as the spacer to improve the electron mobility and the use of dual delta doped layers to improve the device linearity. The developed InGaP/InGaAs PHEMT with very low noise figure and leakage current and very high OIP3 is of great use for wireless communication applications.

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References

1 Wu, C.L., Wang, J.C., and Chang, C.S.: 'Super low noise InGaP gated PHEMT', *IEEE GaAs Dig.*, 2001

2 Hur, K.Y., Hetzler, K.T., McTaggart, R.A., Vye, D.W., Lwmonias, P.J., and Hoke, W.E.: 'Ultralinear double pulse doped AlInAs/GaInAs/InP HEMTs', *Electron. Lett.*, 1996, **32**, (16)

3 Jkalainen, P.K., Witkowski, L.C., and Kao, Y.C.: 'Low-noise low DC power linear FET'. European Microwave Conf. Proc., 1992, Vol. 1, (22), pp. 570–575

4 Okamoto, Y., Matsunaga, K., Kuzuhara, M., and Kanamori, M.: 'Novel InGaP/AlGaAs/InGaAS heterojunction FET for X-Ku band power applications', *IEEE MTT-S Int. Microw. Symp. Dig.*, 1997, 3, pp. 1191–1194

5 Zheng, H.Q., Ng, G.I., Zhang, Y.Q., Radhakrishnan, K., Lee, K.Y., Chee, P.Y., Tse, M.S., Weng, J.X., and Yoon, S.F.: 'High linearity, current drivability and f_{max} using pseudomorphic GaAs double-heterojunction HEMT (DHHEMT)', *Semicond. Electron.*, 1996, pp. 12–14

6 Chu, S.L.G., Huang, J., Struble, W., Jackson, G., Pan, N., Schindler, M.J., and Tajima, Y.: 'A highly linear MESFET', *IEEE MTT-S Int. Microw. Symp. Dig.*, 1991, **2**, pp. 725–728

Link between cross-Wigner distribution and cross-Teager energy operator

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The cross-Teager-Kaiser energy operator for complex-valued signals is defined and a new operator called Ψ_B is introduced. The relationship between the cross-Wigner-Ville distribution and the operator Ψ_B is established. This link results in a simple way to estimate the second conditional moment via the Wigner-Ville distribution. Some important properties of Ψ_B are also presented.

Introduction: The Teager-Kaiser energy operator (TKEO) is a nonlinear, differential operator that computes the energy of a real-valued signal $x(t)$ and is defined in the continuous domain by

$$\Psi_{\rm R}(x) = \left(\frac{dx(t)}{dt}\right)^2 - x(t)\frac{d^2x(t)}{dt^2} \quad (1)$$

or using the dot notation to denote differentiation with respect to independent variable, in this case time t

$$\Psi_{\rm R}(x) = \dot{x}^2 - x\ddot{x} \quad (2)$$

where $x \equiv x(t)$, $\dot{x} = dx(t)/dt$ and $\ddot{x} = d^2x(t)/dt^2$. This energy operator is a very local property of the signal and depends only on the signal and its first and two time derivatives [1]. TKEO is an energy tracking method that has low computational complexity, a very good time resolution and is very easy to implement efficiently. However, it is limited to a monocomponent signal (bandpass signal). This operator has been successfully used in speech analysis [2, 3] and image processing [4]. For example, Maragos *et al.* [3] have used this operator to estimate the amplitude envelope of an AM signal and the instantaneous frequency of an FM signal. To represent the interaction between two real time functions, a second energy-like function, called the cross-Teager-Kaiser operator (CTKEO) has also been defined [1]. This function may be viewed as cross-energy between two real signals. In this Letter, we extend the definition of CTKEO over complex-valued signals and propose a new symmetric operator called Ψ_B. Then we establish the connection between the operator Ψ_B and the cross-Wigner-Ville distribution (CWVD).

Cross-Teager-Kaiser operator: The CTKEO between two real time signals x and y is defined by $\Psi(x, y) = \dot{x}\dot{y} - x\ddot{y}$ and its reverse by $\Psi(y, x) = \dot{x}\dot{y} - y\ddot{x}$. In general this operator is not commutative, $\Psi(x, y) \neq \Psi(y, x)$. If $y = x$, then $\Psi(x, y)$ becomes the continuous operator [1], $\Psi_{\rm R}(x) = \dot{x}^2 - x\ddot{x}$. In the general case, if x and y represents displacements in some motions, the quantity $\Psi(x, y)$ or $\Psi(y, x)$ has dimensions of energy (per unit mass) [5]. This energy-like quantity $\dot{x}\dot{y} - x\ddot{y}$ or $\dot{x}\dot{y} - y\ddot{x}$ was used to analyse the output $\Psi(x, y)$ of the energy operator applied to $(x + y)$ [1].

Extension to complex signals: Definition: The CTKEO of two complex-valued signals x and y, noted by $\Psi_{\rm C}(.,\ .)$, is defined as follows:

$$\Psi_{\rm C}(x, y) = \frac{1}{2}[\dot{x}^*\dot{y} + \dot{x}\dot{y}^*] - \frac{1}{2}[x\ddot{y}^* + x^*\ddot{y}] \quad (3)$$

$$\Psi_{\rm C}(y, x) = \frac{1}{2}[\dot{x}^*\dot{y} + \dot{x}\dot{y}^*] - \frac{1}{2}[y\ddot{x}^* + y^*\ddot{x}] \quad (4)$$

The asterisk denotes complex conjugation. If $x = y$, it is easy to show that the definition proposed by Hamila *et al.* [6] holds, $\Psi_{\rm C}(x) = \dot{x}\dot{x}^* - 0.5[x\ddot{x}^* + x^*\ddot{x}]$. A simple approach to have a symmetric operator, $\Psi_B(x, y)$, is to take the average of $\Psi_{\rm C}(x, y)$ and its reverse $\Psi_{\rm C}(y, x)$:

$$\Psi_B(x, y) = \frac{1}{2}[\Psi_{\rm C}(x, y) + \Psi_{\rm C}(y, x)] \quad (5)$$

$$= \frac{1}{2}[\dot{x}^*\dot{y} + \dot{x}\dot{y}^*] - \frac{1}{4}[x\ddot{y}^* + x^*\ddot{y} + y\ddot{x}^* + y^*\ddot{x}] \quad (6)$$

Proposition 1: Let x and y be two complex signals. $\Psi_B(x, y)$ is a symmetric bilinear form and $\Psi_{\rm C}(x)$ is the associated quadratic form.

Proof:

$$\begin{aligned}
1)\ \Psi_B(y, x) &= \frac{1}{2}[\dot{y}^*\dot{x} + \dot{y}\dot{x}^*] - \frac{1}{4}[y\ddot{x}^* + y^*\ddot{x} + x\ddot{y}^* + x^*\ddot{y}] \\
&= \Psi_B(x, y) \\
2)\ \Psi_B(ax_1 + bx_2, y) &= \frac{1}{2}[a\dot{x}_1^*\dot{y} + b\dot{x}_2^*\dot{y} + a\dot{x}_1\dot{y}^* + b\dot{x}_2\dot{y}^*] \\
&\quad - \frac{1}{4}[ax_1\ddot{y}^* + bx_2\ddot{y}^* + ax_1^*\ddot{y} + bx_2^*\ddot{y} \\
&\quad + ay\ddot{x}_1^* + by\ddot{x}_2^* + ay^*\ddot{x}_1 + by^*\ddot{x}_2] \\
&= \frac{a}{2}[\dot{x}_1^*\dot{y} + \dot{x}_1\dot{y}] + \frac{b}{2}[\dot{x}_2^*\dot{y} + \dot{x}_2^*\dot{y}(t)^*] \\
&\quad - \frac{a}{4}[x_1\ddot{y}^* + x_1^*\ddot{y} + y\ddot{x}_1^* + y^*\ddot{x}_1] \\
&\quad - \frac{b}{4}[x_2\ddot{y}^* + x_2^*\ddot{y} + y\ddot{x}_2^* + y^*\ddot{x}_2] \\
&= a\Psi_B(x_1, y) + b\Psi_B(x_2, y)
\end{aligned}$$

In similar fashion

$$3)\ \Psi_B(x, ay_1 + by_2) = a\Psi_B(x, y_1) + b\Psi_B(x, y_2)$$

$$4)\ \Psi_B(x, x) = \Psi_{\rm C}\ \text{(according to (5))} \quad (7)$$

Ψ_B properties: The operator Ψ_B has the following properties:

1. $\Psi_B(0, x) = \Psi_B(x, 0) = 0$
2. $\Psi_B(a, x) = \Psi_B(x, a) = -(a/2)\Re[\ddot{x}]$
3. $\Psi_B(x + a, y) = \Psi_B(x, y) + \Psi_B(a, y)$
4. $\Psi_B(x + a, x) = \Psi_C(x) - (a/2)\Re[\ddot{x}]$
5. $\Psi_B(ax, y) = a.\Psi_B(x, y)$
6. $\Psi_B(ax, x) = a.\Psi_C(x)$
7. $\Psi_B(a, b) = 0$
8. $\Psi_B(ax, ax) = a^2\Psi_C(x)$
9. $\Psi_B(e^{-j\omega_1 t}, e^{-j\omega_2 t}) = ((\omega_1 + \omega_2)^2/2)\cos(\omega_1 - \omega_2)t$

where a and b are real constants and x and y are complex signals.

Proposition 2: The CTKEO of complex signals x and y is equal to the sum cross-Teager energies of their real and imaginary parts,

$$\Psi_B(x, y) = \Psi_B(x_r, y_r) + \Psi_B(x_i, y_i) \tag{8}$$

where $x(t) = x_r(t) + jx_i(t)$ and $y(t) = y_r(t) + jy_i(t)$

Proof:

$$\begin{aligned}\Psi_B(x, y) = &\frac{1}{2}[(\dot{x}_r - j\dot{x}_i)(\dot{y}_r + j\dot{y}_i) + (\dot{x}_r + j\dot{x}_i)(\dot{y}_r - j\dot{y}_i)] \\ &- \frac{1}{4}[(x_r + jx_i)(\ddot{y}_r - j\ddot{y}_i) + (x_r - jx_i)(\ddot{y}_r + j\ddot{y}_i) \\ &+ (y_r + jy_i)(\ddot{x}_r - j\ddot{x}_i) + (y_r - jy_i)(\ddot{x}_r + j\ddot{x}_i)] \\ \Psi_B(x, y) = &\dot{x}_r\dot{y}_r - \frac{1}{2}[x_r\ddot{y}_r + \ddot{x}_r y_r] + \dot{x}_i\dot{y}_i - \frac{1}{2}[x_i\ddot{y}_i + \ddot{x}_i y_i]\end{aligned}$$

Maragos and Bovik [4] proposed the following TKEO for complex signals:

$$\Psi_C(x) = \|\dot{x}(t)\|^2 - \Re[x(t)^*\ddot{x}(t)] \tag{9}$$

Recently, Hamila *et al.* [6] have proposed another definition for complex signals

$$\Psi_C(x) = \Psi_R(x_r) + \Psi_R(x_i) \tag{10}$$

If $x = y$ and substituting x in (10) and (9), it can easily be shown that (8) holds for both Maragos and Bovik's definition and for that of Hamila *et al.*

Link between CTKEO and CVWD: The CWVD is based on the local cross-correlation $g_{xy}(t, \tau)$ of the complex signals x and y. This instantaneous cross-correlation is given by

$$g_{xy}(t, \tau) = x^*(l_1) \cdot y(l_2) \tag{11}$$

where $l_1 = t - \tau/2$, $l_2 = t + \tau/2$, and τ is the time lag variable.

Proposition 3: Let x and y be two complex signals. g_{xy} is related to Ψ_B by

$$\Psi_B(x, y) = -\frac{\partial^2 g_{xy}(t, \tau)}{\partial\tau^2}\bigg|_{\tau=0} - \frac{\partial^2 g_{xy}{}^*(t, \tau)}{\partial\tau^2}\bigg|_{\tau=0} \tag{12}$$

Proof:

$$\begin{aligned}\frac{\partial g(t, \tau)}{\partial\tau} &= \frac{1}{2}[x^*(l_1)\dot{y}(l_2) - \dot{x}^*(l_1)y(l_2)] \\ \frac{\partial^2 g_{xy}(t, \tau)}{\partial\tau^2} &= \frac{1}{4}[x^*(l_1)\ddot{y}(l_2) - 2\dot{x}^*(l_1)\dot{y}(l_2) + \ddot{x}^*(l_1)y(l_2)] \\ \frac{\partial^2 g_{xy}(t, \tau)}{\partial\tau^2}\bigg|_{\tau=0} &= \frac{1}{4}[x^*(t)\ddot{y}(t) - 2\dot{x}^*(t)\dot{y}(t) + \ddot{x}^*(t)y(t)] \\ &= -\frac{1}{2}\dot{x}^*(t)\dot{y}(t) + \frac{1}{4}[x^*(t)\ddot{y}(t) + \ddot{x}^*(t)y(t)]\end{aligned}$$

In similar fashion

$$\begin{aligned}\frac{\partial^2 g_{xy}^*(t, \tau)}{\partial\tau^2}\bigg|_{\tau=0} &= -\frac{1}{2}\dot{x}(t)\dot{y}^*(t) \\ &\quad + \frac{1}{4}[x(t)\ddot{y}^*(t) + \ddot{x}(t)y^*(t)] \\ -\frac{\partial^2 g_{xy}(t, \tau)}{\partial\tau^2}\bigg|_{\tau=0} - \frac{\partial^2 g_{xy}^*(t, \tau)}{\partial\tau^2}\bigg|_{\tau=0} &= \Psi_B(x, y)\end{aligned}$$

The CVWD of x and y is defined by:

$$W_{xy}(t, \nu) = \frac{1}{2\pi}\int_{\mathbf{R}} q_{xy}(t, \tau)e^{-j\nu\tau}d\tau \tag{13}$$

Proposition 4: Let x and y be two complex signals. The CVWD of x and y is related to the CTKEO by:

$$\Psi_B(x, y) = +\frac{1}{2\pi}\int_{\mathbf{R}} \nu^2[W_{xy}(t, \nu) + W_{x^*y^*}(t, \nu)]d\nu \tag{14}$$

Proof:

$$\begin{aligned}g_{xy}(t, \tau) &= \frac{1}{2\pi}\int_{\mathbf{R}} W_{xy}(t, \nu)e^{-j\tau\nu}d\nu \\ \frac{\partial^2 g_{xy}(t, \tau)}{\partial\tau^2}\bigg|_{\tau=0} &= \frac{1}{2\pi}\int_{\mathbf{R}} \frac{\partial^2[W_{xy}(t, \nu)e^{-j\nu\tau}]}{\partial\tau^2}\bigg|_{\tau=0} d\nu \\ &= -\frac{1}{2\pi}\int_{\mathbf{R}} \nu^2 W_{xy}(t, \nu)d\nu\end{aligned}$$

Thus, $\Psi_B(x, y) = (1/2\pi)\int_{\mathbf{R}}\nu^2[W_{xy}(t, \nu) + W_{x^*y^*}(t, \nu)]d\nu$
if $x = y$ then

$$\Psi_B(x, x) = \frac{1}{\pi}\int_{\mathbf{R}} \nu^2 W_x(t, \nu)d\nu \tag{15}$$

Thus, we relate the TKEO to WVD and this confirms the finding of Hamila *et al.* [6]. The second conditional moment in frequency of the Wigner distribution is given by

$$\langle\nu^2\rangle_t = \frac{1}{|x(t)|^2}\int_{\mathbf{R}} \nu^2 W_x(t, \nu)d\nu \tag{16}$$

Finally

$$\langle\nu^2\rangle_t = \pi\frac{\Psi_B(x, x)}{|x(t)|^2} \tag{17}$$

According to this equation, it is easy to calculate the second conditional of the Wigner distribution using the operator Ψ_B. However, this relation is limited to a monocomponent signal. For a multicomponent signal, bandpass filtering is necessary.

Conclusion: A new operator called Ψ_B is introduced to extend the cross-Teager-Kaiser energy operator over complex-valued signals. We have shown that Ψ_B is a symmetric bilinear form and some of its important properties are presented. We have established the link between the cross-Teager-Kaiser energy operator and cross-Wigner-Ville distribution. For equal signals ($x = y$), the resulting relation is a simple way to calculate the second conditional moment in frequency of a Wigner distribution. However, the proposed method is limited to a monocomponent signal.

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References

1 Kaiser, J.F.: 'Some useful properties of Teager's energy operators'. Proc. ICASSP, Minneapolis, MN, USA, 1993, Vol. 3, pp. 149–152
2 Teager, H.M., and Teager, S.M.: 'Evidence for nonlinear speech production mechanisms in the vocal tract'. Proc. NATO Advanced Study Institute on Speech Production and Speech Modeling, Bonas, France, July 1989, pp. 214–261
3 Maragos, P., Kaiser, J.F., and Quatieri, T.: 'Energy separation in signal modulations with application to speech analysis', *IEEE Trans. Signal. Process.*, 1993, 41, pp. 3025–3051
4 Maragos, P., and Bovik, A.C.: 'Image demodulation using multidimensional energy separation', *J. Opt. Soc. Amer. A*, 1995, **12**, (9), pp. 1867–1876
5 Maragos, P., and Potamianos, A.: 'Higer order differential energy operators', *IEEE Signal Process. Lett.*, 1995, 2, (8), pp. 152–154
6 Hamila, R., Astola, J., Alaya Cheikh, F., Gabbouj, M., and Renfors, M.: 'Teager energy and the ambiguity function', *IEEE Trans. Signal Process.*, 1999, 47, (1), pp. 260–262

Nonlinear signal classification using geometric statistical features in state space

S. Yang

A new methodology in the framework of high-dimensional shape analysis in state space is proposed for nonlinear signal classification. The zero-crossing rate on a Poincare surface of a section is used as a feature. Experiments regarding oceanic signal classification show that the proposed methodology can provide some information not contained in spectra.

Introduction: Nonlinear features play an important role in a variety of applications in terms of signal classification, for instance, oceanic and biomedical signal classification [1, 2]. A major methodology for nonlinear signal analysis is the toolkit used for studying chaotic systems [3, 4]. An essential part of the toolkit is state space reconstruction. By this means, a time series of interest can be embedded into a high-dimensional space, namely state space. The high-dimensional trajectory constructed from the time series contains useful information for nonlinear signal classification [5]. In the current literature, most nonlinear features are based on global measurements of trajectories in the sense of dynamics and geometry. Two representative features in this direction are the Lyapunov exponent and the fractal dimension [1, 2]. Global measurements are limited in that shape details of trajectories do not reflect in the measurements at all. In the case that global measurements are not sufficiently distinct among different classes, the shape details of trajectories become the only clue for the sake of classification. However, research relating to this aspect has not been reported to date. To fill this gap, a new methodology in the framework of high-dimensional shape analysis in state space is proposed for feature extraction. It is a four-step strategy. (i) Embed the time series of interest to a high-dimensional space using state space reconstruction. (ii) Normalise the orientation and position of the high-dimensional trajectory constructed from the time series. (iii) Use a set of Poincare surfaces to cut the trajectory. As a result, the points of intersection on every Poincare surface are highlighted. (iv) Extract shape features from the points of intersection on every Poincare surface. Here, the zero-crossing rate is utilised as a feature extractor. The experimental results regarding oceanic signal classification show that the proposed methodology is able to provide some information not contained in traditional spectral features. As a result, the current solution is augmented.

State space reconstruction: The state space reconstruction performed on a given time series $[S_i]$:$i = 1, 2, \ldots, N_T$ is as follows [3, 4]. First, two parameters, the delay time J and embedding dimension N, should be computed. Then, an N-dimensional vector sequence $[X_j]$:$j = 1, 2, \ldots, M$ can be constructed from the time series by letting $X_j = (S_j, S_{j+J}, S_{j+2J}, \ldots, S_{j+(N-1)J})^T$, where $M = N_T - (N-1)J$. The determination of J and N are still open problems. Here, the computation of J follows [6]. Let $A(k)$ represent the autocorrelation function of the time series, where k denotes the discrete-time step. Once $A(k)$ drops below $A(0)/e$, let $J = k$. The determination of N is subject to applications and will be described later.

Orientation normalisation: To measure similarity among trajectories that are constructed from corresponding time series, the orientation and position of every trajectory should first be normalised. Here, the orientation normalisation is achieved via the following co-ordinate transformation based on principal component analysis [7]. Suppose that $o_1 \geq o_2 \geq \cdots \geq o_N$ are the eigenvalues of XX^T in ascending order, where $X = [X_1, X_2, \ldots, X_M]$, and $U_1, U_2, \ldots, U_N$ the corresponding eigenvectors. Let $\{U_1, U_2, \ldots, U_N\}$ span a new co-ordinate and conduct the following co-ordinate transformation:

$$Y_j = (U_1^T X_j, U_2^T X_j, \ldots, U_N^T X_j)^T \quad (1)$$

with respect to every trajectory point, $j = 1, 2, \ldots, M$.

Position normalisation: Let $Y_j = (y_{j1}, y_{j2}, \ldots, y_{jN})^T$ denote the values of point Y_j, $j = 1, 2, \ldots, M$, and $\bar{Y} = (\bar{y}_1, \bar{y}_2, \ldots, \bar{y}_N)^T$ the centre of the trajectory in the new co-ordinate. The centre is defined as

$$\bar{y}_1 = \frac{m_{1\ldots0}}{m_{0\ldots0}}, \ldots, \bar{y}_N = \frac{m_{0\ldots1}}{m_{0\ldots0}} \quad (2)$$

where

$$m_{p_1 \ldots p_N} = \sum_{j=1}^{M} \prod_{i=1}^{N} y_{ji}^{P_i} \quad (3)$$

is the regular moment of the trajectory points with order $(P_1, P_2, \ldots, P_N)$ [8]. Then, the position normalisation is achieved via the following translation:

$$Y \longleftarrow Y_j - \bar{Y} \quad (4)$$

$j = 1, 2, \ldots, M$.

Poincare surface of section: The Poincare surface of a section is a widely used means for observing trajectories of chaotic attractors. It is a hyperplane that intersects a trajectory at a given position. The points at which a trajectory passes through a Poincare surface are named as points of section. These points reveal shape particularities of the trajectory of interest.

Zero-crossing rate: Assume that a Poincare surface intersecting the ith co-ordinate at position y_0. The zero-crossing rate is defined as

$$Z = \frac{1}{M}\left\{\sum_{j=1}^{M} P[y_{ji} = y_0] + \sum_{j=1}^{M-1} P[(y_{ji} - y_0)(y_{(j+1)i} - y_0) < 0]\right\} \quad (5)$$

where

$$P[Q] = \begin{cases} 1 & \text{if } Q \text{ is true} \\ 0 & \text{if } Q \text{ is false} \end{cases} \quad (6)$$

A Poincare surface can intersect perpendicularly an axis at any position, so the zero-crossing rate is subject to the position of the Poincare surface. Here, we let $Z(L{:}i{:}R)$ represent the zero-crossing rate computed on the Poincare surface that intersects perpendicularly the ith axis at position R with embedding dimension L. For example, $Z(15{:}10{:}0.1)$ means the zero-crossing rate computed on the Poincare surface that cuts perpendicularly the tenth axis at position 0.1 with embedding dimension 15.

Experiments: We used the data set described in [1] to evaluate the performance of the proposed methodology. This data set contains six classes of oceanic signals, 100 samples per class. The data length of each sample is 3264. Every sample was normalised to possess unit energy in the preprocessing. Features in the proposed framework and traditional spectral features are examined separately using the data set. The selected features in the proposed framework are $\{Z(5{:}3{:}0.001)$, $Z(15{:}3{:}-0.002)$, $Z(15{:}5{:}0)$, $Z(15{:}7{:}-0.001)$, $Z(15{:}15{:}0.002)$, $Z(15{:}15{:}0.005)\}$. Fig. 1 shows the feature distribution of class A–F in terms of feature 1, 5 and 6. It can be seen that distinction between every two different classes exists. It must be mentioned that not only the above selected features but also many of the other features in this