

Studying relationships from the perspective of chaos theory

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Studying relationships from the perspective of chaos theory

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The study of relationship emotions, a set of emotional and psychological responses that arise in a relationship, can help develop more humanized artificial intelligence, improve human–computer interaction, and even create more immersive experiences in virtual and augmented reality. Due to the nonlinear and feedback-driven nature of relational affect, which aligns closely with chaos theory, and the ability of leaky integrate-and-fire (LIF) neuron models to simulate dopamine-related electrical activity in brain nuclei, this study innovatively integrates both approaches. By linking the membrane potential signals of LIF neurons to relational affect equations, it achieves a refined modeling of the mechanisms underlying relational affect generation. This paper adds the LIF neuron model to the relationship emotion model to construct a new LIF relationship emotion model (LRM). The effect of the parameters in the LRM on the relationship emotions generated by the model is investigated using numerical analysis. This includes the firing behavior produced by LIF neurons and a study of relationship emotions produced by different initial relationship emotion states under the same conditions. Finally, the feasibility of LRM is verified using a digital signal processing (DSP) platform. This process not only verifies the feasibility of LRM but also provides new ideas and methods for future research in affective computing and human–computer interaction.

Keywords: relationship, emotion, chaos, neural network, DSP platform

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1. Introduction

Love is a complex emotional encounter, a distinctive yet universal sentiment,[1] involving love, passion, intimacy, and attachment. Being in love is not only about physical attraction but also about mental and emotional connection.[2,3] The brain secretes large amounts of dopamine when producing the emotion of love.[4] Dopamine is a neurotransmitter secreted by the brain, mainly in the central nervous system and peripheral nervous system; it is involved in regulating the body's emotions, movement, and physiological functions, and also regulates the cardiovascular system.[5] The nucleus accumbens is a round, flat structure that acts as the stimulus control center of the brain.[6] It accelerates the production of dopamine, which fills the brain with a sense of well-being, euphoria, and desire. As dopamine levels increase, euphoria and desire intensify. When dopamine reaches a certain level, the individual exhibits love behavior.[7] Understanding relationship emotions helps people to identify and manage them better and reduces the incidence of anxiety and depression.[8] Research has shown that positive emotional experiences can enhance mental health, while negative emotions can lead to psychological problems.[9] It is also possible that research in areas such as psychology and neuroscience can help develop new treatment programs, such as affective therapy and emotion regulation tools.[10–12] Meanwhile, in the fields of artificial intelligence and human–computer interaction, understanding human emotions can help create more emotionally intelligent systems. Therefore, the study of relationship emotions is of great importance.

The process of creating relationship emotions is highly analogous to chaos theory. A romantic relationship can be viewed as a complex system involving the interaction of emotional, behavioral, and environmental factors of two or more individuals.[13] In chaos theory, small changes can trigger large changes in the system,[14–16] similar to how, in a relationship, minor frictions or misunderstandings in communication can lead to dramatic swings in emotions. Emotional changes in love are often non-linear, and fluctuations may be influenced by many non-linear factors, such as personal experience, external pressure, and the social environment. This is consistent with chaos theory, which states that small differences in initial conditions can produce different outcomes.[17] Chaos theory emphasizes uncertainty and unpredictability in complex systems.[18–20] In a relationship, emotions are often fraught

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with variables, and the behavior and reactions of both parties cannot be fully predicted.[21] This unpredictability makes relationships full of surprises and challenges, sometimes leading to unexpected results. There are many feedback mechanisms in romantic relationships; for example, the behavioral and emotional responses of partners affect each other, creating positive or negative feedback.[22] This cycle is an important element in chaos theory, emphasizing the interplay of dynamical changes in a system.[23–26] In general, chaos theory provides a new perspective for understanding relationship emotions and allows us to explore the complexities and dynamics of relationships in greater depth.[27–32]

Many researchers have established mathematical models of love based on chaos theory to study love emotions.[33–37] In 2005, a general model of happiness was proposed by Sprott *et al.*[38] By studying the dynamic behavior and properties of the model, it was found that the existence of chaos implies a certain degree of unpredictability within the dynamic model of happiness. The model has been applied to many scenarios for research and illustration. In 2011, Barley *et al.*[39] examined the nonlinear dynamics of romantic relationships. They found that such relationships can be influenced by various factors, including individual emotions, communication styles, and environmental changes, and that these factors tend to be nonlinear and interact with each other. Existing chaos theory-based models of love predominantly focus on macro-level emotional dynamics, failing to integrate the physiological foundations at the neuronal level. This results in an insufficient linkage between the models and the biological mechanisms underlying genuine emotional experiences, coupled with an inadequate parametric representation of individual differences, such as self-worth and partner support. This paper combines their research to make the feedback of the relationship model more reasonable by integrating it with the mathematical model of leaky integrate-and-fire (LIF) neurons. The improved love emotion model can be used to study the generation of love emotion through individual neuron parameters, self-value, support for love objects, and other aspects. The model is also used to explain a variety of relationship phenomena.

In summary, there is a great need for research on relationship emotions, and to make the relationship model more complete, we combine it with the LIF neuron model that represents the hippocampus and apply it to research relationship phenomena. The methodology used in this paper to study relationship emotions is described in Section 2. The relationship model of this paper and its topology are described in detail in Section 3. The effects of various parameters with different meanings on relationship emotions are analyzed in detail in Section 4. The feasibility of the simulation is verified using a digital signal processing (DSP) platform in Section 5, which lays the foundation for future integration with artificial intelligence, machine learning, and other digital technologies.

2. Methodology

This paper adds two LIF neuron models, representing a male and a female, to the romantic relationship model. The love signals produced by the other person are combined with their own signals as the stimulus signals in the LIF. The results produced by each iteration of the LIF neuron model representing a male and a female are incorporated into A_1 and A_2 in the relationship equation, enhancing the relevance of each system dimension.

Define "cycle" as two people not in a romantic mood and "chaos" as two people in a romantic mood.[40] The initial value represents the initial state of the two people's romantic emotions. By varying the corresponding parameters, it is possible to investigate whether people with different personalities and states can develop romantic feelings.

3. The establishment of a love model

3.1. Two-way love model

Two LIF neuron models are used to simulate the activity of brain nuclei of two individuals. The brain receives emotional stimuli from the partner, and the brain nuclei accelerate the secretion of dopamine, stimulating the corresponding behavior of the individuals. The topology of the relationship emotion model proposed in this paper is shown in Fig. 1.

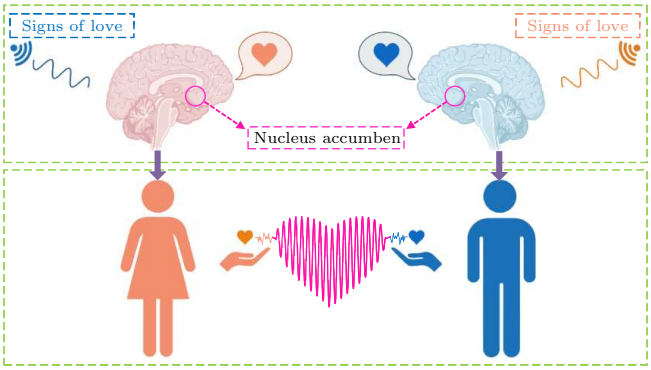


Fig. 1. Topology of relationship generation.

The LIF neuron model is a mathematical model used to simulate the behavior of biological neurons. It simulates changes in neuronal membrane potential through a simplified electrical circuit. Membrane potentials vary over time and are affected by input signals and their intrinsic dynamics. The following equation describes its dynamic behavior:

$$\tau V(i+1) = -(V(i) - V_{\text{rest}}) + RI(t). \tag{1}$$

Here, $V(i)$ is the membrane potential, V_{rest} is the resting potential, R is the membrane resistance, $I(t)$ is the input current, and τ is the time constant. The model is designed to simulate the electrical activity and spike-generation behavior

of neurons. This model combines the dynamics of neuronal membrane potentials with the mechanism of pulse (or action potential) generation.

Relationship emotions occur between two independent individuals; therefore, at least two dimensions are required when constructing a mathematical model of relationship emotions. In this regard, this paper proposes a two-dimensional relationship emotion model as follows:

$$\begin{cases} X_1 = -eX_1 + g\sin\left(X_2(1-hA_1{}^2)\right), \\ X_2 = -jX_2 + k\left[\dfrac{1}{1+\mathrm{e}^{-X_1(1-h_1A_2{}^2)}}\right], \end{cases} \tag{2}$$

where e and j are non-negative numbers representing the extent to which an individual internalizes self-worth. g and k indicate the level of support provided by the partner. X_1 and X_2 represent the emotional intensities of the male and female partners, respectively, while A_1 and A_2 correspond to the membrane potential dynamics of LIF neurons, directly reflecting the electrical activity associated with dopamine secretion in the nucleus accumbens. A_1 and A_2 are real numbers. Combining Eqs. (1) and (2), since $g\sin(X_2(1-hA_1^2))$ and $k\left\{1/[1+\mathrm{e}^{-X_1(1-h_1A_2^2)}]\right\}$ denote the response to passion, and passion is generated by the stimuli provided by the love object, let A_1 and A_2 represent the membrane potentials of the other LIF neuron, respectively. The final mathematical model of the relationship is shown below:

$$\begin{cases} \dot{x} = -\frac{1}{a}(x-b) + \frac{1}{a}R_1\sin(y+z), \\ \dot{y} = -\frac{1}{c}(y-d) + \frac{1}{c}R_2\left[\frac{1}{1+\mathrm{e}^{-(x+w)}}\right], \\ \dot{z} = -ez + g\sin\left(w(1-hy^2)\right), \\ \dot{w} = -jw + k\left[\frac{1}{1+\mathrm{e}^{-z(1-h_1x^2)}}\right]. \end{cases} \tag{3}$$

3.2. Regretful love model

In a relationship between two people, although one person may express positive emotional signals, the other person does not necessarily provide positive feedback and may even feel disgusted. Therefore, the relationship emotion model is designed to represent not only situations in which two people are mutually in love, but also situations in which the relationship is imperfect. The topology of imperfect relationship emotions is shown in Fig. 2. The topology corresponding to males liking females while females dislike males is shown in Fig. 2(a); the topology corresponding to females liking males while males dislike females is shown in Fig. 2(b); and the topology corresponding to males and females having no favorable feelings toward each other is shown in Fig. 2(c).

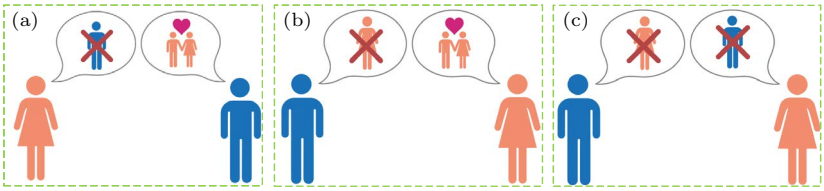


Fig. 2. Topology of the regretful love model. (a) Males like females, while females dislike males. (b) Females like males, while males dislike females. (c) Both parties dislike each other.

4. Chaos in the relationship emotions

4.1. Effect of film resistor $R_{1,2}$ on the system

The combination of membrane resistance, capacitance, and time constant determines the propagation speed of action potentials. High membrane resistance is usually accompanied by slower signaling. Therefore, it is necessary to analyze the membrane resistance. The parameters are selected as $a = 0.9$, $b = -5.5$, $c = 5$, $d = -2$, $e = 0.1$, $g = 1.08$, $h = 1$, $h_1 = 1$, $j = 0.9$, $k = 1$, $R_1 = 9$, and $R_2 = 12$. With the LEs and BD representing the changes in membrane resistance R_1 of female LIF neurons, as shown in Fig. 3,[41] the relationship emotion system is in a chaotic state when $R_1 \in (8.86, 9.09) \cup (9.2, 14.6)$, and perfect relationship outcomes are reached when the membrane resistance R_1 is within this range. The relationship emotion system is in a cyclic state when $R_1 \in (8, 8.86) \cup (9.09, 9.2) \cup (14.6, 15)$, and perfect relationship outcomes are not achieved when the membrane resistance R_1 is in this range.

The attractor generated by changes in membrane resistance R_1 is shown in Fig. 4. The periodic attractor with $R_1 = 8.5$ is shown in Fig. 4(a), and the chaotic attractors with $R_1 = 9$ and 14 are shown in Figs. 4(b) and 4(c).

With LEs and BD representing the changes in membrane resistance R_2 of male LIF neurons, as shown in Fig. 5, a wide range of cyclic phenomena occurs as R_2 varies in this relationship-emotion system. Chaos occurs only to a lesser extent with changes in R_2, meaning that a perfect relationship is reached under those conditions. This phenomenon is consistent with social observations.[42]

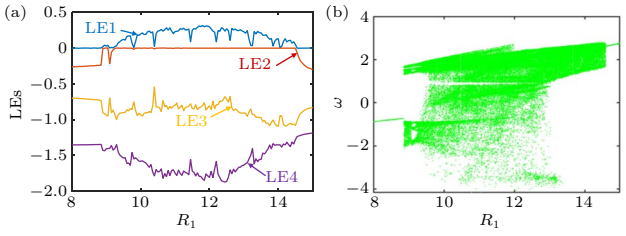


Fig. 3. LEs and BD as membrane resistance R_1 increases in female LIF neurons. (a) LEs. (b) BD.

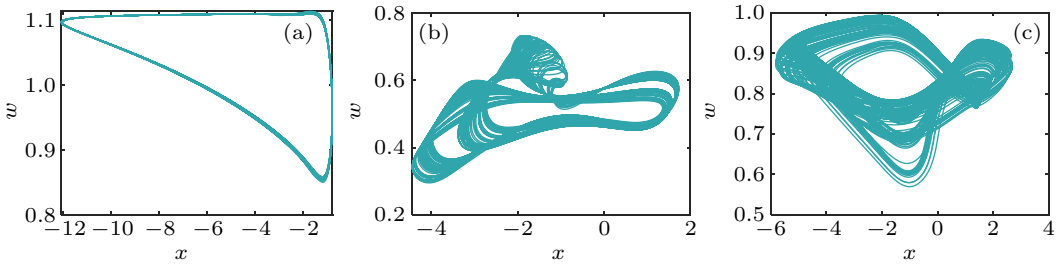


Fig. 4. Attractors with increasing membrane resistance R_1 in female LIF neurons. (a) $R_1 = 8.5$. (b) $R_1 = 9$. (c) $R_1 = 14$.

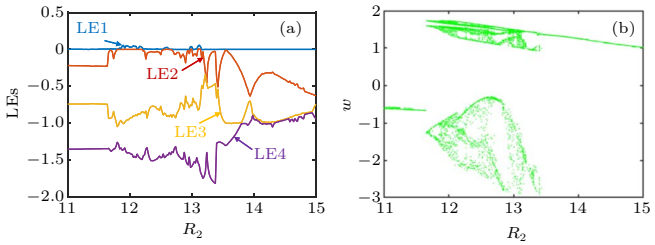


Fig. 5. LEs and BD as membrane resistance R_2 increases in male LIF neurons. (a) LEs. (b) BD.

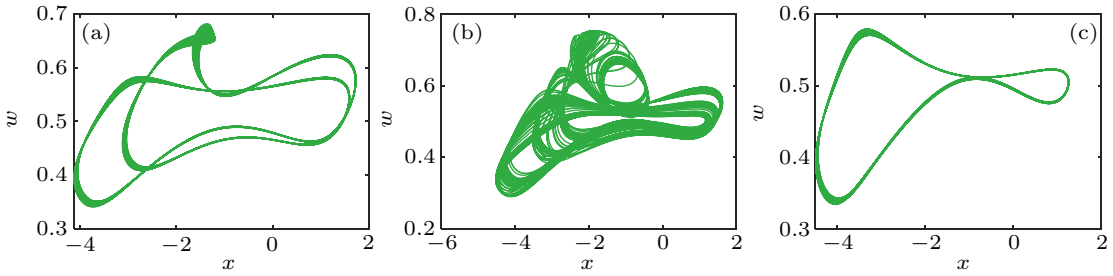


Fig. 6. Attractors with increasing membrane resistance R_2 in male LIF neurons. (a) $R_2 = 11.7$. (b) $R_2 = 12.5$. (c) $R_2 = 14$.

The attractors generated as the membrane resistance R_2 varies are shown in Fig. 5. The periodic attractors at $R_2 = 11.7$ and 14 are shown in Figs. 6(a)–6(c), and the chaotic attractor at $R_2 = 12.5$ is shown in Fig. 6(b).

4.2. Firing patterns of the system

Understanding neuronal firing patterns can help design more effective brain-computer interfaces (BCIs) and facilitate the integration of neuroscience and engineering.[43–47] The firing patterns of neurons are closely related to learning and memory, providing insight into the biological basis of these processes. In this paper, some interesting electrical discharges are observed during the analysis of parameters in LIF neurons representing males and females. The selected parameters are $a = 0.9$, $b = -5.5$, $c = 5$, $d = -2$, $g = 1.08$, $h = 1$, $h_1 = 1$, $j = 0.9$, $k = 1$, $R_1 = 9$, and $R_2 = 12$.

When $e = 0$, the x-sequence (red), representing the female, and the y-sequence (green), representing the male, exhibit cyclic burst discharge behavior, as shown in Fig. 7(a). When $e = 0.1$, the x and y sequences undergo chaotic burst discharge behavior, as shown in Fig. 7(b). When $e = 0.2$, periodic spike discharge behavior occurs in the x and y sequences, as shown in Fig. 7(c).

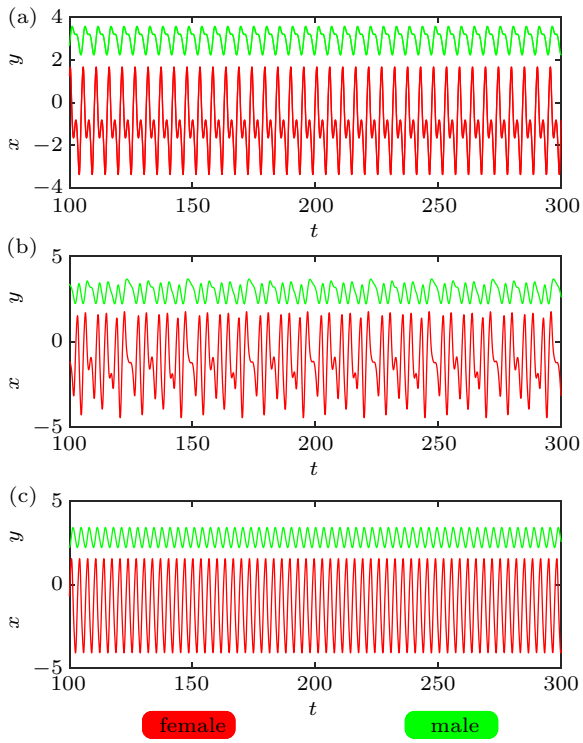


Fig. 7. Firing pattern diagrams of the LIF neuron model in this system. (a) Cyclic burst discharge ($e = 0$), corresponding to emotional stagnation under a lack of self-worth. (b) Chaotic burst discharge ($e = 0.1$), corresponding to dynamic emotional interaction under healthy self-worth. (c) Cyclic spike discharge ($e = 0.2$), corresponding to emotional rigidity under excessive self-worth (selfishness).

4.3. The effect of the degree of self-worth on the emotions of relationships

People with a high sense of self-worth usually show more confidence in social interactions, which in turn creates a positive attraction to others, making their socialization smoother and more successful. The same principle applies when two people are in love. Therefore, it is necessary to analyze and explain the parameters that represent the sense of self-worth in the relationship emotion system.

The LEs and BD that indicate an increase in the female's sense of self-worth e are shown in Fig. 8. As observed in Fig. 8, the system is in a cyclic state when the female's sense of self-worth $e = 0$, indicating that relationship emotions do not arise when there is no sense of self-worth. When $e \in (0, 0.12)$, the relationship emotion system is almost always in a chaotic state, and the probability of generating relationship emotions is very high within this range. When $e \in (0.12, 0.15)$, the system returns to a cyclic state, as the sense of self-worth becomes particularly high, evolving from self-confidence to ego. This is consistent with the observation that relationship emotions are difficult to produce in egoistic personalities.

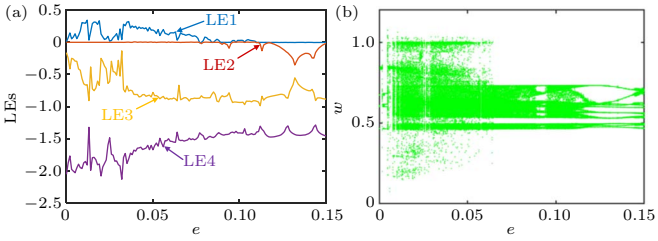


Fig. 8. LEs and BD as the female's sense of self-worth increases. (a) LEs. (b) BD.

When the self-worth parameter $e = 0$, the z–w attractor, representing the emotion of love, is in a cyclic state, as shown in Fig. 9(a). In this case, the female in the system fails to produce the emotion of love due to low self-esteem. The z–w attractor for relationship emotions when $e = 0.1$ is shown in Fig. 9(b), and relationship emotions are successfully generated under this level of self-worth. When $e = 0.12$, no relationship emotion occurs because the sense of self-worth is too high and the personality shifts from self-confidence to ego; the corresponding z–w attractor is shown in Fig. 9(c).

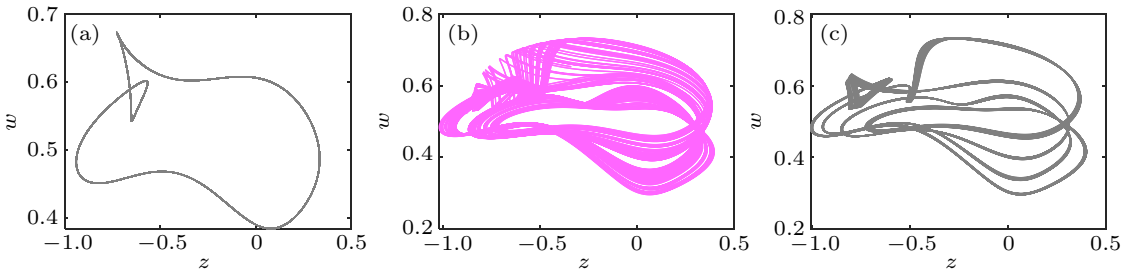


Fig. 9. Attractors as the female's sense of self-worth increases. (a) $e = 0$. (b) $e = 0.1$. (c) $e = 0.12$.

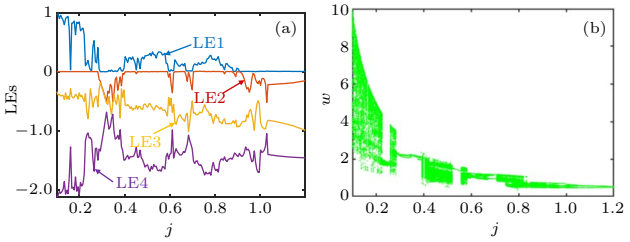


Fig. 10. LEs and BD as the male's sense of self-worth increases. (a) LEs. (b) BD.

The LEs and BD indicate an increase in the parameter j, representing the male's sense of self-worth, as shown in Fig. 10. The system does not operate properly when $j \in (0, 0.1)$, indicating that males with low self-esteem have difficulty developing relationship emotions. When $j \in (0.1, 0.91)$, the relationship emotion system is almost always in a chaotic state, suggesting that this range is most conducive for males to generate relationship emotions. When $j \in (0.91, 1.2)$, similar to the female parameter e, the sense of self-worth is excessively high, evolving into ego, and it becomes difficult to develop relationship emotions.

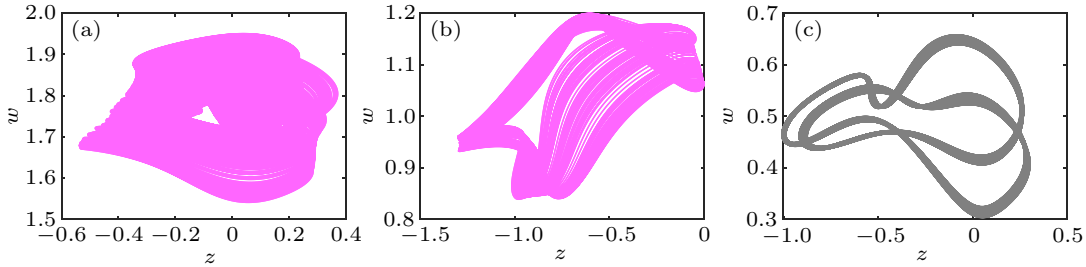


Fig. 11. Attractors as the male's sense of self-worth increases. (a) $j = 0.23$. (b) $j = 0.7$. (c) $j = 1$.

Along with the z–w attractor indicating changes in the male's sense of self-worth is shown in Fig. 11. The z–w attractor when $j = 0.23$ is shown in Fig. 11(a), successfully generating relationship emotions under this level of self-worth. The z–w attractors when $j = 0.7$ and $j = 1$ are shown in Figs. 11(b) and 11(c), respectively.

4.4. The effect of partner support on relationships

In the course of a relationship between two people, in addition to self-confidence, the partner's support is also necessary. Therefore, it is important to analyze the level of partner support. When the parameter $g = 0$, representing the level of female support, is considered, the relationship emotion curves between males and females are shown in Fig. 12(a). The curves fluctuate slightly for a short period and then settle down. The relationship emotion curve when the parameter $k = 0$, representing the level of male support, is shown in Fig. 12(b); it exhibits behavior similar to that when $g = 0$. These results indicate that relationship emotions cannot arise without the support of either party.

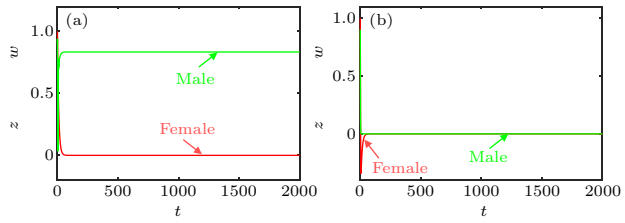


Fig. 12. Relationship emotion curves at different levels of partner support. (a) Female support level $g = 0$. (b) Male support level $k = 0$.

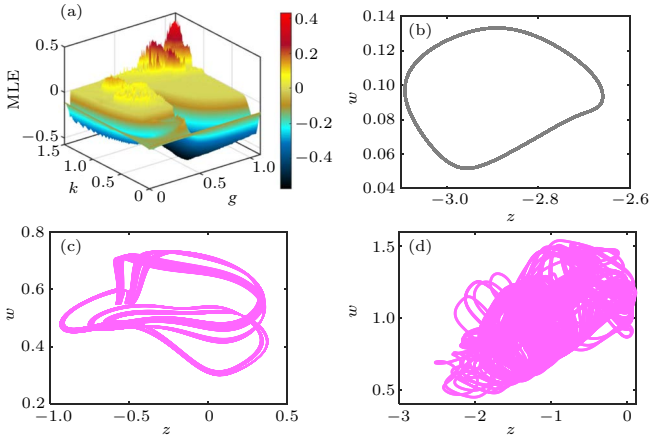


Fig. 13. Bi-parameter LEs and attractors with increasing partner support. (a) Bi-parameter LEs. (b) $g = 0.6$, $k = 0.2$. (c) $g = 1$, $k = 1$. (d) $g = 1.1$, $k = 1.5$.

Lower partner support also affects relationship emotions, so it should be examined in more detail. The bi-parameter LEs that increase with the parameters g and k, indicating the levels of support from the partners, are shown in Fig. 13(a). This relationship emotion system experiences a large range of chaos when male support levels $g \in (0.81, 1.1)$ and female support levels $k \in (1, 1.5)$, suggesting that relationship emotions are more likely to stabilize and develop successfully within this range. The z–w period attractor for relationship emotion when $g = 0.6$ and $k = 0.2$ is shown in Fig. 13(b), which fails to produce relationship emotions under this set of support levels. The z–w chaotic attractors when $g = 1$, $k = 1$ and $g = 1.1$, $k = 1.5$ are shown in Figs. 13(c) and 13(d), where the two parties support each other, develop mutual affection, and the relationship is successful.

4.5. Male and female without love for each other

It is also possible to fail to develop relationship emotions even when both self-confidence and support are present. Since relationship emotions arise only between individuals who reciprocate affection, if Individual A never develops relationship emotions toward Individual B, Individual B is unlikely to elicit emotions from A regardless of effort. This phenomenon is studied by controlling the initial values. Let the initial value be $(x, y, z, w) = (\alpha, \beta, \theta, \gamma)$ (α, β are real numbers, $\gamma > 0$), $k = 0$, and let the other parameters take arbitrary values to indicate that the male prefers the female while the female dislikes the male. The relationship emotion curve for the female is shown in Fig. 14(a), corresponding to the relationship topology in Fig. 2(a). The curve shows that female relationship emotion returns to calm after a brief fluctuation. Similarly, let the initial value be $(x, y, z, w) = (\alpha_1, \beta_1, \gamma_1, 0)$ (α_1, β_1 real, $\gamma_1 > 0$), $g = 0$, and let other parameters be arbitrary to indicate the female prefers the male while the male does not choose the female. The male's relationship emotion curve is shown in Fig. 14(b), corresponding to the relationship topology in Fig. 2(b); it eventually returns to calm. There is also a situation where both individuals dislike each other, defined as $g = k = 0$ and $z = w = 0$. In this case, the relationship emotion curve is shown in Fig. 14(c), corresponding to the relationship topology in Fig. 2(c). This system rationalizes these phenomena through numerical analysis.

4.6. Different initial relationship emotions produce different results

This section examines how initial relationship emotions affect outcomes when one individual initially lacks emotions and parameters vary without changing other conditions. The parameters are chosen as $a = 0.9$, $b = -5.5$, $c = 5$, $d = -2$, $e = 0.1$, $g = 1.08$, $h = 1$, $h_1 = 1$, $j = 0.9$, $R_1 = 9$, $R_2 = 12$. Define $(1, 5, 2, 0)$ as the initial state where the male lacks relationship emotion and $(1, 5, 0, 2)$ for a female with no initial emotion. The BD with increasing female support k in these two states is shown in Fig. 15(a), demonstrating that different initial states under identical conditions produce completely different relationship emotions. The z–w attractor when $k = 1$ is shown in Fig. 15(b), where the initial state $(1, 5, 2, 0)$ produces no relationship emotion. The z–w attractor when $k = 1.23$ is shown in Fig. 15(c), with both initial states generating relationship emotions. The z–w attractor when $k = 1.88$ is shown

in Fig. 15(d), and the initial state $(1,5,0,2)$ produces no relationship emotion.

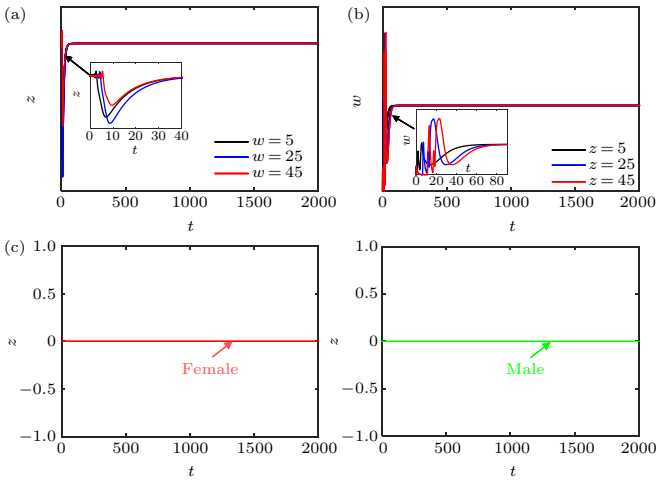


Fig. 14. Relationship emotion fluctuation graphs when partner support and favorability are absent. (a) Relationship curve corresponding to Fig. 2(a). (b) Relationship curve corresponding to Fig. 2(b). (c) Relationship curve corresponding to Fig. 2(c).

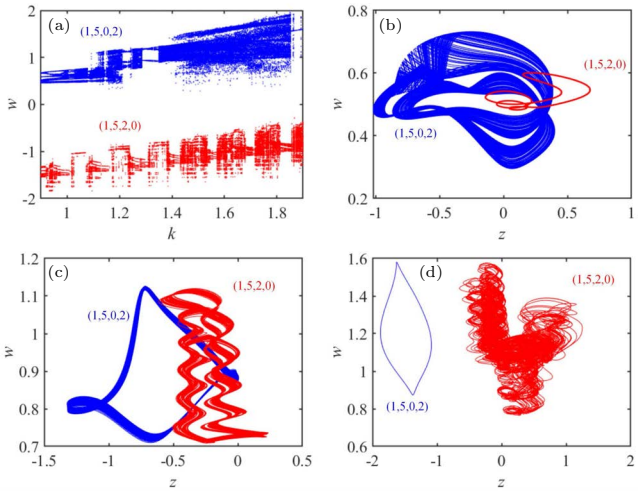


Fig. 15. Relationship emotion outcomes from different initial emotional states. (a) Coexistence branch diagram (BD). (b) $k = 1$. (c) $k = 1.23$. (d) $k = 1.88$.

5. DSP implementation

DSP provides higher computational accuracy, is less susceptible to human factors, exhibits better resistance to noise and interference, and lays a foundation for future integration with artificial intelligence, machine learning, and other digital technologies. Therefore, it is necessary to verify the chaotic relationship emotion system using DSP. The process of connecting the DSP hardware in this study is shown in Fig. 16(a). The program is downloaded from a computer to the TMS320F28335 processor. The DAC8552 digital-to-analog converter transforms the digital signals generated by the processor into analog signals, which are then output to an oscilloscope. The DSP and the oscilloscope display of the attractor are shown in Fig. 16(b). The different outputs of the DSP are shown in Fig. 16(c).

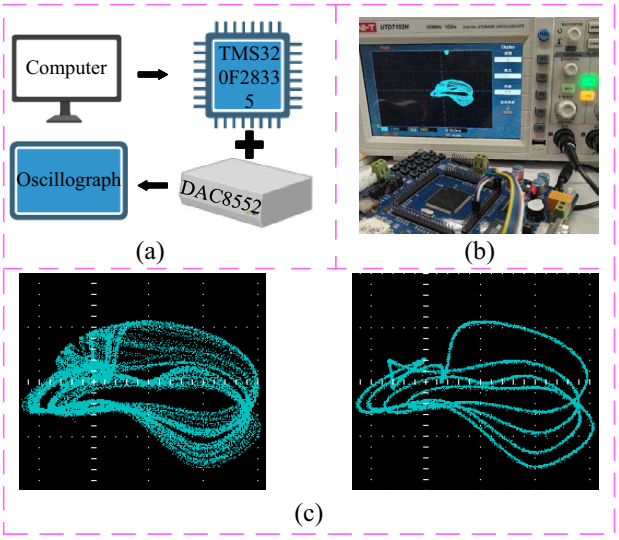


Fig. 16. DSP implementation results. (a) Hardware implementation steps. (b) DSP and oscilloscope display of the attractor. (c) Different attractors obtained from the DSP.

6. Conclusion

In this paper, the LIF neuron model is incorporated into the relational sentiment model to construct a new LIF relationship emotion model (LRM). Chaotic phenomena indicate the generation of relationship emotions, while cyclic phenomena indicate the absence of such emotions. Through numerical analysis, it was found that the LRM exhibits chaotic behavior when the membrane resistance R_1 of the female LIF neuron is within an appropriate range, corresponding to the formation of a successful relationship. For the membrane resistance R_2 of the male LIF neuron, a wider range of cyclic phenomena is observed, which aligns with the observation that males tend to rely more on logic and rationality in social interactions and are relatively less sensitive to emotional fluctuations.

The effect of the degree of self-worth on relationship emotions is also analyzed. It is found that when the sense of self-worth lies within a certain range, the LRM is in a chaotic state, generating relationship emotions. When the sense of self-worth is too high, the LRM exhibits cyclic behavior, and relationship emotions fail to emerge. The effect of partner support on relationship emotions is further examined. The LRM produces relationship emotions when support levels are within an appropriate range, whereas insufficient support prevents the emergence of such emotions. Finally, the absence of mutual affection is investigated. By controlling the initial conditions, it is observed that different initial relationship emotion states lead to completely different outcomes under identical parameters.

In summary, by introducing the LIF neuron model into the relationship model and analyzing each parameter in detail, this paper provides new methods and perspectives for studying relationship emotions. This work contributes to a better understanding and management of relationship emotions and in-

forms the design of artificial intelligence and human-computer interaction systems.

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