*Article*

# Multidimensional Emotion Recognition Based on Semantic Analysis of Biomedical EEG Signal for Knowledge Discovery in Psychological Healthcare

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**Abstract:** Electroencephalogram (EEG) as biomedical signal is widely applied in the medical field such as the detection of Alzheimer's disease, Parkinson's disease, etc. Moreover, by analyzing the EEG-based emotions, the mental status of individual can be revealed for further analysis on the psychological causes of some diseases such as cancer, which is considered as a vital factor on the induction of certain diseases. Therefore, once the emotional status can be correctly analyzed based on EEG signal, more healthcare-oriented applications can be furtherly carried out. Currently, in order to achieve efficiency and accuracy, diverse amounts of EEG-based emotions recognition methods generally extract features by analyzing the overall characteristics of signal, along with optimization strategy of channel selection to minimize the information redundancy. Those methods have been proved their effectiveness, however, there still remains a big challenge when applied with single channel information for emotion recognition task. Therefore, in order to recognize multidimensional emotions based on single channel information, an emotion quantification analysis (EQA) method is proposed to objectively analyze the semantically similarity between emotions in valence-arousal domains, and a multidimensional emotion recognition (EMER) model is proposed on recognizing multidimensional emotions according to the partial fluctuation pattern (PFP) features based on single channel information, and result shows that even though semantically similar emotions are proved to have similar change patterns in EEG signals, each single channel of 4 frequency bands can efficiently recognize 20 different emotions with an average accuracy above 93% separately.

**Keywords:** electroencephalogram; biomedical signal; emotion recognition; partial fluctuation pattern; machine learning; single channel

## 1. Introduction

Emotions as the reaction to the internal or external incident, is consisted with multiply feelings, thoughts and actions, which mixed up with psychological and physiological respondence [1]. Therefore, the emotions which caused by the internal or external stimuli can then be observed through the biological signals such as electrocardiogram (ECG), electromyogram (EMG), galvanic skin response (GSR), electroencephalogram (EEG) and etc. [2–5], which directly reflect on the emotional status of individuals. And different emotions might cause different changes in the biological signals. Homeostasis is been studied to prove that different emotions might be caused by internal or external stimuli, emotions such as love, anger and fear might be activated by the environment stimuli, while fatigue, pain and hunger are due to the body needs. Moreover, neurologist discovered that anger, fear, sadness and disgust have their own nervous system activities [6], moreover, emotions are associated with neurotransmitters,

such as anger is caused by the combination of low serotonin, high dopamine and high norepinephrine, yet when experiencing the feeling of shame, those three neurotransmitters are in a low level, and all three in a high level when excitement is felt [7]. Moreover, evidence shows that the positive emotions are more active in the left prefrontal cortex [8], interestingly, anger which regarded as negative emotion, also activates the left prefrontal cortex [9]. Some neuropsychologists suggest that the both regions of the brain are responsible for the emotions, however, the left frontal brain is more associated with positive emotions and social functions, while the right frontal brain is dealing with the emotions that related to survival, which caused the asymmetric frontal brain activity [10].

Since evidences support that diverse emotions might be caused by different brain activities, from the characteristic of EEG, emotions can be recognized by the differentia of respondence. Nowadays, the wearable EEG devices contained with one or several electrodes that attached on the individual's skin can precisely record the electrical activity from the brain which can be convenient for further analysis. Generally, the analysis of EEG signal is based on different frequency bands as: delta, theta, alpha, beta and gamma. Each frequency band represents different function of body [11,12] as delta is regarded associated with sleep and concentrated task, theta is associated with inhibition of elicited responses, alpha can represent the status of relaxation and also the inhibition control, beta ranges from calm to stressed and obsessive, including thinking, focus, alert and anxious, while gamma is associated with cognitive competence and revealed a denser network connection when involved with different emotional states than other frequency bands. Studies show that the beta and gamma have been observed with a higher performance on recognizing emotions compared to other three bands. Other than the different frequency bands, selection of electrodes also might bring about different results.

Expect EEG signal, the diversity of emotion itself is also complex. Plutchik [13] once proposed an emotional wheel which suggests that emotions are formable, with eight basic emotions placed on the emotional wheel, and each two as the polarity of one and another, the follow-up emotions can be then combined within those basic emotions in different degree. Therefore, emotions are regarded as relatable to each other, and psychologists attempt to quantify emotions by using methods such as factor analysis to map those emotions into a more limited dimension [14]. Generally, a two-dimensional coordinate map is applied with valence and arousal to quantify emotion, where valence is to describe the emotion degree of negative to positive, while arousal is to describe how energized or dispassionate the emotion is.

In this paper, we aim to explore the correlation between emotion and EEG signal, and which can be furtherly applied on the healthcare of individual. Since some complex emotions are regarded as combination of basic emotions, which indicts the existence of similarity between them. Therefore, we mainly focus on the following questions:

- Whether there are similar brain activities when similar emotions occurred?
- Can those similar emotions be correctly distinguished based on EEG signal?
- Can each electrode successfully recognize different emotions?
- Are only high frequency bands suitable for recognizing emotions?
- Can partial fluctuation pattern (PFP) features be efficient on recognition of emotions?

To resolve those questions above, the emotion quantification analysis (EQA) method is proposed, which can objectively map emotion on the valence-arousal domains and reflect the relevance of similar emotions. Then an EEG-based Multidimensional Emotion Recognition (EMER) model is proposed to analyze the composition of EEG signal, and conducted a pattern approach on recognition of emotions based on PFP features.

## 2. Related Work

Currently, most studies on EEG-based emotion recognition are focusing on selection of features, classification methods, optimization of channel selection and emotion categories which can be recognized by EEG signal.

Related studies have proved that diverse features and multiple machine learning methods are efficient on the classification task. Chen et al. [15] proposed a combination method of spatial pattern and wavelet packet decomposition on recognition of EEG-based emotions, which is aim for reducing fluctuations and differences on the signals, the data contain with sad and happy labels, as a result, it reaches accuracy of 86.2%. Doma et al. [16] compared several performances of machine learning methods on recognition of EEG-based emotions, including support vector machine (SVM), k-nearest neighbor (KNN), linear discriminant analysis (LDA), logistic regression (LR) and decision tree (DT), and as a result, SVM has a better performance with accuracy ranges from 54% to 71%. Ali et al. [17] proposed a combination method contains with wavelet energy, modified energy and wavelet entropy features on detection of emotion for analysis the possibility of ambient assisted living. The labels of emotion are divided into four types as HVHA, HVLA, LVHA and LVLA according to the distribution of valence-arousal model. And in the experiment, three classification methods including quadratic discriminant analysis (QDA), KNN, SVM are applied, and as a result, SVM has a higher performance of the accuracy rate on recognition of the emotion at averagely 83%. Yin et al. [18] proposed a feature selection approach due to the combination of heterogeneous features might on the other hand reduce the accuracy, 440 features are adopted into the feature ranking method as transfer recursive feature elimination (T-RFE), and result shows that, only 10 features are significant for classification of emotions. Murugappan et al. [19] used different classification methods on the feature extraction of EEG as fuzzy C-means (FCM) and fuzzy K-means (FKM), six emotions including: anger, disgust, fear, happy, sad and surprise are labeled in the dataset, and features are selected with energy and entropy, as a result, those methods performed well on the clustering emotions. Li et al. [20] explored the performance of different features on classification of emotions, 18 features of two types including time-frequency domain feature and non-linear dynamical system features are analyzed on different datasets. As a result, Hjorth parameter: mobility, Hjorth parameter: complexity and maximum power spectral frequency performed well in beta band, and the combination of linear features is better compared to non-linear features in each band. Asghar et al. [21] proposed a feature selection approach based on bag of deep features, which can reduce the features of data according to the k-mean clustering, as a result, when the clustering group is 10, the SVM has reached separately 77% and 93% of accuracy on recognition of emotions based on DEAP dataset and SEED dataset, where DEAP dataset contains with EEG signals with self-rating emotion values of valence-arousal domain, and SEED dataset contains with EEG signals with three different emotion labels as "Positive", "Negative" and "Neutral". Zhuang et al. [22] proposed a method based on empirical mode decomposition (EMD) to extract the multidimensional information features on Intrinsic Mode Functions (IMFs) for EEG emotion recognition, and result shows that those three features as the first difference of IMF's times series, the first difference of IMF's phase and the normalized energy of IMF are proved to be efficient on recognition of EEG-based emotion based on DEAP dataset.

Mainly, multi-channel is applied on EEG-based emotion recognition due to the combination of different channel can outcome great results. However, single channel is more application-oriented which has an affordable price and convenient usage in daily life. Jalilifard et al. [23] conducted an experiment on the classification of emotion based on the recorded signals from FP1 channel with the stimuli of horror and relaxing movies. Three emotions status are observed as neutral, relaxation and fear. And by using the KNN classification method, the result shows that with 46 features, the accuracy has reached averagely 94%. Taran et al. [24] used a correlation analysis and frequency-based filtering method on emotion recognition of happy, fear, sad and relax status from single-channel

signals, electrodes of FP1, FP2, F3, F4, F7, F8, T3, T4, T5 and T6 are selected as single-bipolar channel, furthermore, the result shows that the proposed method has an overall accuracy of 90.63%. Wu et al. [25] analyzed the functional connectivity pattern of emotion recognition based on EEG signals and eye movements, also, pointed out that the strength feature is proved to be outperformed than the differential entropy in single channel, as a result, that emotions of happiness, disgust, fear, sadness, and neutrality have detected significant functional connectivity, and the accuracy on DEAP, SEED and SEED-V are separately reached at 86%, 95% and 84%. Wan et al. [26] conducted an experiment that used the single-channel signal to detect major depressive disorder with machine learning methods, the result shows that signals collected from FP1 electrode is outperformed than FP2 electrode in prescreening of major depression disorder, and the Classification and Regression Tree combining with genetic algorithm (CART-GA) has a great performance than other machine learning methods. Song et al. [27] proposed a dynamical graph convolutional neural networks on EEG emotion recognition, by analyzing the intrinsic correlation between different electrodes, discriminative features can be discovered and performed efficiently on emotion recognition task.

Generally, studies based on emotion types are mainly discrete or quantified in valence-arousal domains, for some experiments only recorded the objectively self-rating emotion values instead of emotion labels. Ismail et al. [28] analyzed four emotions as anger, sad, happy and surprise with the characteristic of different frequency bands, and the result shows that anger is associated with right side of brain in theta band, sad is related to right posterior region of brain with delta and theta bands, happy is noticeable in the middle region with alpha band, and surprise is clearly observed in delta and theta bands. Hu et al. [29] analyzed ten positive emotions in EEG signal as: amusement, awe, gratitude, hope, inspiration, interest, joy, love, pride and serenity, cluster analysis is conducted on those ten emotions with three cluster groups as encouragement, playfulness and harmony based on the objective rating of valence, arousal, familiarity and liking. As a result, the playfulness group has reached the highest accuracy of nearly 90%, while encouragement and harmony have separately 84% and 85% of accuracy. Li et al. [30] used KNN to cluster the emotional value of valence-arousal in DEAP dataset as several emotion categories, and analyzed the performance of channel combination with number of 10, 14, 18 and 32. As a result, 32 number of channels has the highest accuracy. Generally, studies of EEG-based emotion recognition mainly analyzed several emotions such as neutral, positive and negative, or happy, sad, anger and etc. [31–35]. Other than the self-conducted experiments to analyze EEG-based emotions, the DEAP and SEED datasets are wildly applied [36–40], SEED datasets have given the exact emotion labels, but the categories of emotions are generally within 5, on the other hand, DEAP dataset uses valence and arousal to quantify the emotion value, and cluster analysis methods are commonly applied to group those coordinate into several emotion labels.

Even though a quantity of studies has proved the accuracy on recognition EEG-based emotion, but generally applied with channel combination strategy, along with feature selection of overall evaluation on the signal [41]. Moreover, the emotion categories that have been recognized based on EEG are quite few and blurry in clustered groups. Therefore, a thorough study based on single channel of recognition on diverse emotion categories can give more insights into this field, and more applications such as healthcare of individuals can be extended.

## 3. Motivation

Compared with question-answering approach of emotion recognition, EEG-based emotion recognition can be more objective, which can avoid certain occasions where individuals might not be fully comprehended or expressed on how they feel which compromise the recognition accuracy. Therefore, from the physiology signa, more information and features can be analyzed to better interpret the actual emotional status of individual. Once the feelings of individual are truly recognized, applications such as

music therapy, healthcare robot, etc. can be more efficiently applied for the healthcare of individual.

Currently the mainstream approaches on recognition of EEG-based emotions conducted an overall evaluation on the signal, however, which might cause the loss of partial features on the signal, therefore, we come up with a hypothesis that brain activities might occur same or similar fluctuation patterns when individuals are experiencing the same or similar emotional status, however, some complex emotions which influenced by external factors such as morality might be insignificant for observation. Therefore, we proposed an EMER model which applied with PFP features on recognizing EEG-based emotions. Moreover, in order to objectively evaluate the emotional status, the emotion quantification analysis (EQA) method is proposed to map emotions on valence-arousal domains.

Firstly, similarity matrixes are obtained which contain with questionnaire and semantics analysis about the correlation between emotions, and the emotional mapping is conducted based on emotional similarity quantification (ESQ) algorithm to obtain the emotion distribution in valence-arousal domains. Secondly, data preprocessing is conducted including emotion quantification and signal decomposition. Then, the criterial rules for recognition multidimensional emotions are discovered for the extraction of PFP features. Lastly, the support vector machine (SVM) is applied to verify the pattern approach for recognition of EEG-based emotions. The procedure of the novel pattern approach is shown at Figure 1.
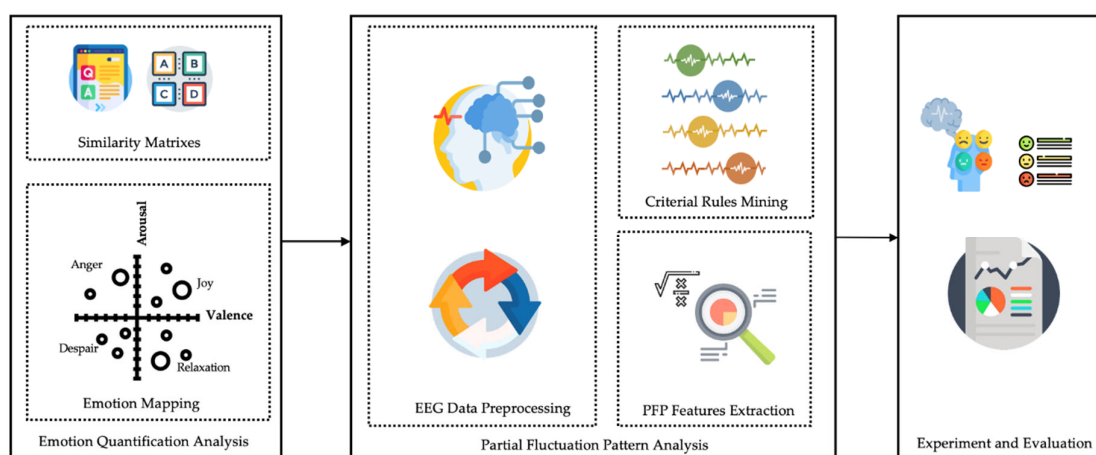


**Figure 1.** The Novel Pattern Approach for Recognition of EEG-based Emotion.

## 4. Emotional Quantification Analysis

In this section, the emotional quantification analysis (EQA) method is conducted based on the emotional similarity quantification (ESQ) algorithm which is proposed to analyze the correlation between emotions, in which each emotion is mapped in the valence-arousal domains according to the emotional similarity matrixes including a questionnaire and a lexicon-based semantic analysis about the emotional similarity.

### 4.1. Emotional Similarity Matrixes

In this section, the emotional similarity matrixes are obtained as the foundation of emotional quantification. Two emotional domains as valence and arousal are selected for further emotion mapping process. Valence represents the negative or positive degree of emotion, and arousal represents the intensity of emotion. According to our previous work [42–44], a 21-dimensional emotion wheel is proposed with a lexicon-based semantic analysis method. The 21 emotions are: "Joy", "Intimacy", "Trust", "Confidence", "Concentration", "Anxiety", "Insecurity", "Fear", "Surprise", "Sadness", "Pain",

"Despair", "Tired", "Shame", "Disgust", "Anger", "Passion", "Gratitude", "Hope", and "Relaxation".

To be more precise and objective on quantifying those emotions, an online questionnaire on the similarity of those 21 emotions is conducted with 151 participants (79 males and 75 females), and 134 of them have obtained the bachelor degree or beyond, aged between 20 and 35, and none of the participants have been majored in any courses that related to psychology. In the questionnaire, we adopted the same procedure as Russell proposed [45] that for each one of the 21 emotions, participant is required to select the most relatable or similar category among eight basic emotions based on their first impression. The eight basic emotion categories are: "Pleasure", "Excitement", "Arousal", "Distress", "Misery", "Depression", "Sleepiness", and "Contentment". The questionnaire result of the emotional similarity is shown at Table 1. It can be observed from the Table 1 that 21 emotions have been closely chosen within adjacent categories.

**Table 1.** Questionnaire Result of Emotional Similarity.

| Emotion | Category | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Pleasure | Excitement | Arousal | Distress | Misery | Depression | Sleepiness | Contentment |
| Joy | 87 | 40 | 7 | / | / | / | / | 17 |
| Intimacy | 47 | 63 | 8 | / | / | 1 | 2 | 30 |
| Trust | 52 | 6 | 1 | 1 | 2 | / | 6 | 83 |
| Confidence | 33 | 8 | 22 | 2 | 2 | 1 | / | 83 |
| Concentration | 11 | 9 | 20 | 2 | 2 | 3 | 65 | 39 |
| Anxiety | 3 | 3 | 44 | 47 | 14 | 40 | / | / |
| Insecurity | 2 | 6 | 56 | 40 | 12 | 33 | 1 | 1 |
| Fear | 2 | 6 | 73 | 34 | 24 | 11 | 1 | / |
| Surprise | 42 | 72 | 32 | 1 | 1 | 2 | / | 1 |
| Sadness | 2 | 1 | 1 | 12 | 55 | 78 | 2 | / |
| Pain | 1 | 1 | 3 | 69 | 42 | 32 | 3 | / |
| Despair | 1 | / | 1 | 33 | 57 | 57 | 2 | / |
| Tired | 2 | 1 | 1 | 9 | 2 | 36 | 100 | / |
| Shame | 3 | 3 | 5 | 52 | 58 | 27 | 3 | / |
| Disgust | 2 | 2 | 3 | 18 | 22 | 61 | 42 | 1 |
| Anger | 2 | 22 | 4 | 49 | 52 | 21 | / | 1 |
| Manic | 7 | 64 | 53 | 9 | 7 | 10 | / | 1 |
| Passion | 7 | 64 | 68 | 3 | 3 | 1 | / | 5 |
| Gratitude | 37 | 5 | 2 | / | 1 | / | 3 | 103 |
| Hope | 26 | 7 | 17 | 2 | / | / | 31 | 68 |
| Relaxation | 33 | 6 | 1 | / | / | 1 | 50 | 60 |

The semantic similarity matrix of those 21 emotions and 8 basic emotion categories is based on the emotional lexicon-based corpus from our previous work, semantic similarity is calculated according to synonym set which labels emotion words as a synonymous set when those words are under the same or similar definition. The similarity value is between 0 and 1.

*4.2. Emotion Mapping*

In this section, the 21 emotions are quantified and mapped into valence-arousal domains based on the similarity matrixes. The parameters that involved in the quantification process are listed in Table 2.

**Table 2.** Parameters in Emotion Mapping Process.

| Parameter | Definition |
|---|---|
| $FS$ | The final similarity matrix. |
| $QS$ | The questionnaire similarity matrix. |
| $SS$ | The semantic similarity matrix. |
| $MP_j$ | The top $j$th similarity value. |
| $Ang$ | The angle of emotion in valence-arousal domains |
| $OA$ | The angle of basic emotion category in valence-arousal domains. |
| $RQ_{(x,y)}$ | Reference coordinate based on $QS$. |
| $RS_{(x,y)}$ | Reference coordinate based on $SS$. |
| $AQ_{(x,y)}$ | The actual coordinate of emotion in valence-arousal domains. |

Firstly, the matrixes of questionnaire and semantic similarity as $QS$ and $SS$ are multiplicated to form the final similarity matrix $FS$ according to Equation (1):

$$FS_{(i,j)} = QS_{(i,j)} \times SS_{(i,j)}, \tag{1}$$

where $FS_{(i,j)}$ represents the similarity value of $i$th emotion in $j$th categories from the final similarity matrix, $QS_{(i,j)}$ represents the similarity value of $i$th emotion in $j$th categories from the questionnaire similarity matrix, and $SS_{(i,j)}$ represents the similarity value of $i$th emotion in $j$th categories from the semantic similarity matrix.

Secondly, since the valence-arousal domains is divided into 8 octants based on the basic categories, each emotion is distributed into one of octant area according to the top two maximum values in $FS$, and the angle of each emotion as $Ang$ in valence-arousal domains is calculated based on the octant angle of most similar category as $OA$ and the similarity ratio of adjacent categories according to Equation (2):

$$Ang = OA + \frac{45}{\left(\frac{MP_1}{MP_2} + 1\right)}, \tag{2}$$

where $MP_1$ and $MP_2$ are referred to the top two maximum similarity values of emotion of adjacent categories in $FS$ clockwise.

Thirdly, in order to analyze more objective coordinate of emotion in valence-arousal domains, two reference coordinates as $RQ_{(x,y)}$ and $RS_{(x,y)}$ are calculated based on $Ang$ and similarity matrixes of $QS$ and $SS$ according to Equations (3,4):

$$RQ_{(x,y)} = (QS_{(i,j)}, QS_{(i,j)} \times \tan(\frac{Ang}{180} \times \pi)), \tag{3}$$

$$RS_{(x,y)} = \left( \frac{SS_{(i,j)}}{\cos\left(\frac{45 - Ang}{180} \times \pi\right)} \times \cos\left(\frac{Ang}{180} \times \pi\right), \frac{SS_{(i,j)}}{\cos\left(\frac{45 - Ang}{180} \times \pi\right)} \times \sin\left(\frac{Ang}{180} \times \pi\right) \right), \tag{4}$$

Finally, the actual coordinate of emotion as $AQ_{(x,y)}$ is calculated based on $RQ_{(x,y)}$ and $RS_{(x,y)}$ according to Equation (5):

$$AQ_{(x,y)} = (min\left(RQ_{(x)}, RS_{(x)}\right) + \frac{\left|RQ_{(x)} - RS_{(x)}\right|}{2}, min\left(RQ_{(y)}, RS_{(y)}\right) + \frac{\left|RQ_{(y)} - RS_{(y)}\right|}{2}), \tag{5}$$

where function $min()$ is to select the minimum value.

Once the actual coordinate of each emotion is calculated, all 21 emotions can be mapped in the valence-arousal domains, as seen from the Figure 2.
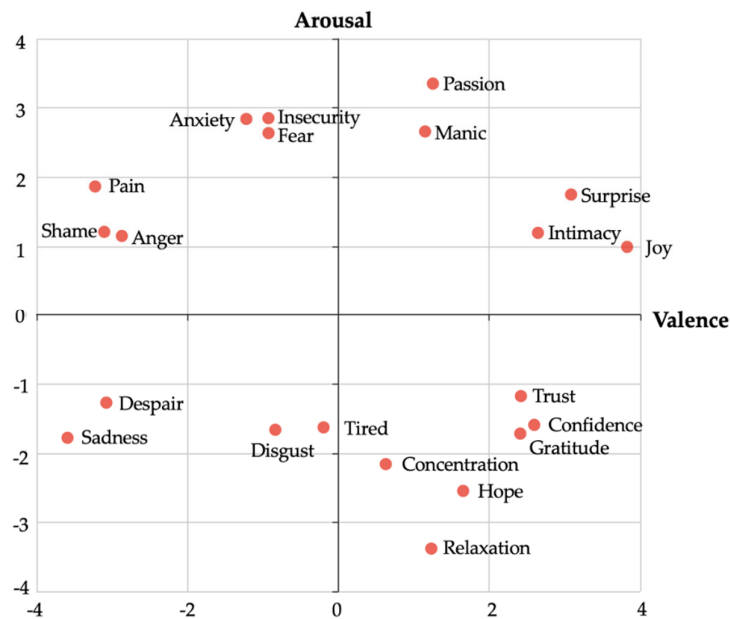
**Figure 2.** Emotion Mapping in Valence-Arousal Domains.

### 4.3. Emotional Similarity Quantification Algorithm

The emotional similarity quantification (ESQ) algorithm is designed to map the emotion based on similarity matrix, and with a great adaptability to applied it on other emotions, the ESQ algorithm can efficiently map them on the valence-arousal domains. The pseudo code of ESQ is shown at Algorithm 1.

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**Algorithm 1. ESQ**

**Input:**
*QS, SS, OA*
**Output:**
*AQS*
1:   **Begin**
2:   *FS* = new array [length(*QS*)[0], length(*QS*)[1]];
3:   *OAs* = new array [8];
4:   **for** $i = 0$, $i <$ length(*QS*)[0], $i$++ **do**
5:    **for** j = 0, j < length(*QS*)[1], j ++ do
6:     $FS$ += $[QS_{(i,j)} * SS_{(i,j)}]$;
7:     *OAs*[j] = j * (360/length(*QS*)[1]);
8:    **end for**
9:   $MP = [\max(FS_{(i,j)})[0], \max(FS_{(i,j)})[1]]$;
10:   $OA = OAs[\text{index}(\max(FS_{(i,j)}))]$;
11:   $Ang = OA + 45/(MP[0]/MP[1] + 1)$;
12:   $RQ(x,y) = (QS_{(i,j)}, QS_{(i,j)} * \tan(Ang/180 * \pi))$;
13:   $RS(x) = SS_{(i,j)}/\cos((45-Ang)/180 * \pi) * \cos(Ang/180 * \pi)$;
14:   $RS(y) = SS_{(i,j)}/\cos((45-Ang)/180 * \pi) * \sin(Ang/180 * \pi)$;
15:   $AQ(x, y) = (\min(RQ(x), RS(x)) + |RQ(x)-RS(x)|/2, \min(RQ(y), RS(y)) + |RQ(y)-RS(y)|/2)$;
16:   $AQS$ += $[AQ(x, y)]$;
17: **end for**

## 5. EEG-based Multidimensional Emotion Recognition Model

In this section, the EEG-based multidimensional emotion recognition (EMER) model is proposed based on the PFP features, in which, the significant serial change patterns of amplitude in EEG signal are analyzed and obtained to train for the recognition criteria rules of multidimensional emotions. Instead of analyzing the overall features in each signal, the EEG signal is split into segments where each part contains single or continuous wave crests and wave troughs. Furthermore, the PFP features are extracted based on the criterial rules for the recognition of emotion.

### 5.1. Data Preprocessing

In this section, the EEG signals are preprocessed for further analysis. Firstly, wavelet transform is applied to obtain the separate frequency bands as: alpha, beta, gamma and theta (DEAP does not contain with delta band). Secondly, the detection technique of wave crest and trough is adopted on each frequency band, amplitude information about the wave crest and trough of each signal are reserved, therefore, signal is split into multiple segments, and each contains one or continuous wave crest or trough. Thirdly, amplitude information on each segment is evaluated according to its amplitude value, 5 evaluation levels are proposed to rank each wave crest and trough from "A" to "E", where "A" represents the highest level of amplitude value, and accordingly to the other 4 levels. The evaluation levels are depended on the highest absolute amplitude value of each signal, and equally distributed as adding 20% of the amplitude value accordingly to 5 levels. For example, when a signal with highest absolute amplitude value of 1, those wave crests or troughs of which have reached at or above absolute amplitude value of 0.8, will be evaluated as level "A", and so to other levels, therefore, each segment is transformed into sequence of "A" to "E". However, in order to discover more significant partial fluctuation patterns of EEG signal on each emotion, denoising is conducted to remove the low amplitude information which remains an abundant amount in the sequences and yet might be insignificant in the classification and compromised to its performance, therefore, each sequence is split into partial fluctuation patterns once "E" occurred, then each partial fluctuation pattern is formed with 4 evaluation level of "A" to "D". Lastly, the valence and arousal value of each signal is calculated with the coordinate distance to each of 21 emotions, and each signal is signed to emotion label with the minimal distance, also the partial fluctuation patterns within the signal are attached with the same emotion label.

### 5.2. Recognition Criteria of Multidimensional Emotions

In this section, the criteria rules of recognition on each EEG-based emotion are trained based on association rule learning, the frequent pattern growth (FP-growth) algorithm is conducted to discover the criteria rules of emotions among partial fluctuation patterns. Firstly, each partial fluctuation pattern is calculated with its frequency that appeared in dataset, and for those patterns which have a greater support value than the threshold are reserved. Secondly, reserved patterns are formed as multiple serial sequences, and the frequency of each sequence is calculated, for those which have a greater confidence value than the threshold are reserved as criteria rules, and the confidence is regarded as the intensity value of the rule. Thirdly, the relevance value between each reserved pattern is calculated which refers to the possibility that a former pattern and a latter pattern occurred at the same time. Therefore, for the possibility value is greater than the threshold, and the former one is already existed in the criteria rule set, then those two pattern are combined as a potential rule to the criteria rule set, and the multiplication of the confidence of former one and the possibility value is regarded as the intensity value of the potential rule.

Once all the criteria rules are obtained, clustering is conducted due to some rules have attached with multiple emotion labels. Firstly, for rules only attached with single emotion, are labeled as the "Representative". Secondly, for rules contained with all

emotions, the standard deviation of rule intensity is calculated, if the standard deviation is smaller than the threshold, those rules are labeled as "Common", which refers to that the rule is commonly occurred among all emotions. Thirdly, for rest of the rules, the emotion distance and standard deviation of those distance values are calculated, if the average distance and standard deviation are smaller than the thresholds, those rules are labeled as "Similar". And to furtherly refine the "Similar" label, 9 subcategories are designed according to the valence-arousal domains, the definitions of those 9 subcategories are listed at Table 3.

**Table 3.** Subcategories of "Similar" Rules.

| Subcategory | Definition |
|---|---|
| HA | Emotions clustered in the first and second quadrant |
| LA | Emotions clustered in the third and fourth quadrant |
| HV | Emotions clustered in the first and fourth quadrant |
| LV | Emotions clustered in the second and third quadrant |
| HVHA | Emotions clustered in the first quadrant |
| HVLA | Emotions clustered in the second quadrant |
| LVLA | Emotions clustered in the third quadrant |
| LVHA | Emotions clustered in the fourth quadrant |
| Similarity | Emotions clustered in one quadrant with close distance |

*5.3. Extraction of Partial Fluctuation Patterns Features*

In this section, partial fluctuation pattern (PFP) features of each EEG signal are analyzed based on the criterial rule set. Due to the partial fluctuation patterns under each signal is existed as single sequence, which only represents a partial change pattern in the signal, however, the criterial rules contain with combination of several sequences. Therefore, the sliding window technique is applied to form the partial fluctuation pattern sequences where the partial fluctuation patterns of each signal are combined orderly. The maximum combination number of partial fluctuation patterns is based on the maximum number of jointed sequences in criteria rule. Once all combinations of partial fluctuation pattern sequences of each signal are obtained, a bidimensional hash searching strategy is conducted to optimize the matching process. And 5 PFP features as: the quantity of PFP, the intensity of PFP, the density of PFP, the repetition rate of PFP, and the polynomial rate of PFP are extracted for further recognition process. The parameters that involved in the calculation of PFP features are listed at Table 4.

**Table 4.** Parameters in Calculation of PFP Features.

| Parameter | Definition |
|---|---|
| $MN$ | The matched number of PFP sequences. |
| $Acc$ | The accumulation of intensity values in matched PFP sequences. |
| $Den$ | The ratio of the $MN$ to the number of PFP sequences. |
| $Rep$ | The repetitive rate of the same matched rules. |
| $Pol$ | The occurred rate of matched polynomial rules. |
| $Int_i$ | Intensity value of $ith$ matched PFP sequence. |
| $Itm$ | The number of PFP in signal. |
| $Mx$ | The maximum length in criterial rule. |
| $Sm$ | The number of same matched PFP sequences. |
| $Ml_j$ | The number of matched PFP sequences with combination length of $j$. |

The quantity of PFP as $MN$ is referred to the matched number of partial fluctuation pattern sequences among the criterial rules.

The intensity of PFP as *Acc* is referred to the accumulation of intensity values in matched partial fluctuation pattern sequences, and the calculation is according to Equation (6):

$$Acc = \sum_{i=1}^{MN} Int_i \tag{6}$$

The density of PFP as *Den* is referred to the ratio of the *MN* to the total combined number of partial fluctuation pattern sequences, and the calculation is according to Equation (7):

$$Den = \frac{2 \times MN}{(2 \times Itm - Mx) \times (Itm - Mx + 1)} \tag{7}$$

The repetition rate of PFP as *Rep* is referred to the ratio of the number of same matched partial fluctuation pattern sequences to *MN*, and the calculation is according to Equation (8):

$$Rep = \frac{Sm}{MN} \tag{8}$$

The polynomial rate of PFP *Pol* is referred to the ratio of the number of matched polynomial partial fluctuation pattern sequences to *MN*, and the calculation is according to Equation (9):

$$Rol = \frac{\sum_{j=2}^{Mx} Ml_j}{MN} \tag{9}$$

*5.4. Partial Fluctuation Pattern Quantification Algorithm*

The partial fluctuation pattern quantification (PFPQ) algorithm is applied to discover the criteria rules of recognition of EEG-based emotions. The pseudo code of PFPQ is shown at Algorithm 2.

| **Algorithm 2. PFPQ** |
|---|
| **Input:** |
| EEG signals as *ES* |
| **Output:** |
| Criteria rule for recognition of emotions as RR and PFP features as PFPs |
| 1:　**Begin** |
| 2:　**for** c = 0, $c < 32$, *c*++ **do** |
| 3:　　Transform $ES_c$ with Wavelet transform into 4 bands as $WES_c$; |
| 4:　　**for** $i = 0$, $i < 4$, *i*++ **do** |
| 5:　　　Detect wave crest and trough of $WES_{c,i}$ as $WCT_{c,i}$; |
| 6:　　　Transform $WCT_{c,i}$ according to the amplitude to A-E as $AE_{c,i}$; |
| 7:　　　$RE_{c,i} = AE_{c,i}.split("E")$; |
| 8:　　　Build tree structure of $RE_{c,i}$ based on frequency as $RETree_{c,i}$; |
| 9:　　　Set support threshold as $st_{c,i}$, confidence threshold as $ct_{c,i}$; |
| 10:　　**for** $k = 0$, $k < length(RETree_{c,i})$, $k$ ++ **do** |
| 11:　　　Search sequence on tree structure as *seq*, and frequency of *seq* as *fseq*; |
| 12:　　　**if** *fseq* > $st_{c,i}$ **then** |
| 13:　　　　RR += [*seq, fseq*]; |
| 14.　　　Add next tree node to *seq* as *seq-nod*, the frequency of seq-nod as *fnod*; |
| 15:　　　**if** *fnod* > $ct_{c,i}$ **then** |
| 16:　　　　AR += [*seq-nod, fnod*]; |
| 17:　　　**end if** |
| 18:　　**end if** |
| 19:　**end for** |

```
20:    RR += AR;
21:    srt = new array[9];
22:    for p = 0, p < length(RR), r ++ do
23:      if length(RRₚ) == 1 then
24:        Label RRₚ as "Representative" rule;
25:      else do Calculate emotional similarity of RRₚ as es;
26:        if es matches threshold value in srt then
27:          Label RRₚ as subcategory of similar rule;
28:        end if
29:      end if
30:    end for
31:    PFPs = new array [];
32:    Joint REc,i as a bidimensional hash set of combined sequences CSS;
33:    for s = 0, s < length(CSS), s++ do
34:      for r = 0, r < length(RR), r++ do
35:        for ss = 0, ss < length(CSS[s]), ss++ do
36:          if CSS[s][ss] == RRᵣ[0] then
37:            MN++;
38:            Acc += RRᵣ[1];
39:            MR[s] += [RRᵣ[0]]
40:            if CSS[s][ss] in MR then
41:              Sm++;
42:            end if
43:          end if
44:        end for
45:      end for
46:    end for
47:    Den = (2*MN)/((2*length(REc,i)-length(CSS)) * (length(REc,i)-length(CSS) + 1));
48:    Rep = Sm/MN;
49:    Pol = (MN-MR[0])/MN;
50:    PFPs = [MN, Acc, Den, Rep, Pol]
51: end for
52: return RR
```

## 6. Experiment

In this section, the experiments are based on DEAP dataset [46]. The evaluation of similarity of partial fluctuation patterns is conducted to verify the objective correlation between emotions from the semantic level and physiological level. Meanwhile, the PFP features are extracted into EMER model to evaluate the model performance and feasibility of the novel pattern approach on recognition of emotions, the power spectral density (PSD) feature of EEG signal is also calculated for a comparison experiment. Moreover, the brain activities of multidimensional emotions are analyzed for further correlation analysis on the similarity of emotions.

### 6.1. Evaluation of Similar Fluctutation Patterns

In this section, the evaluation of similarity of partial fluctuation patterns is conducted to verify the hypothesis that whether semantically similar emotions reveal similar change patterns in signal. As the criteria rules under each emotion have already been clustered into 9 subcategories according to the similarity matrixes with EQA method, the intensity value of those criteria rules which represents the frequency of the partial fluctuation pattern occurred under each emotion, therefore, if the occurrence appeared equally among the emotions that under same subcategory, the existence of similar changes among

similar emotion can be verified. The standard deviation of intensity values under each subcategory is calculated, and of which is smaller than the threshold is regarded as commonly occurred patterns under each subcategory, and the similarity proportion of each subcategory is calculated based on the ratio of the number of commonly occurred patterns to the number of criterial rules. The similarity proportion of emotion subcategories are shown at Figure 3.
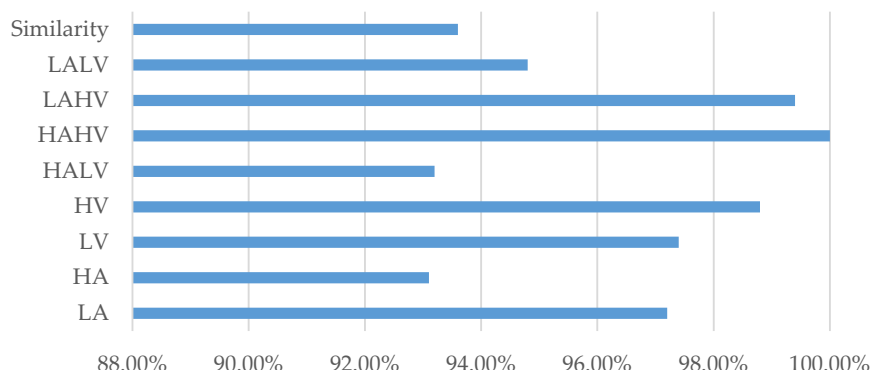


**Figure 3.** Similarity Proportion of Emotion Subcategories.

From Figure 3, it can be observed that all nine groups have the similarity proportion above 92%, which indicates that for those similar emotions, a large quantity of partial fluctuation patterns occurred equally among those emotions. To a certain extent, the proportion can verify the hypothesis that those semantically similar emotions have similar change patterns in EEG signal.
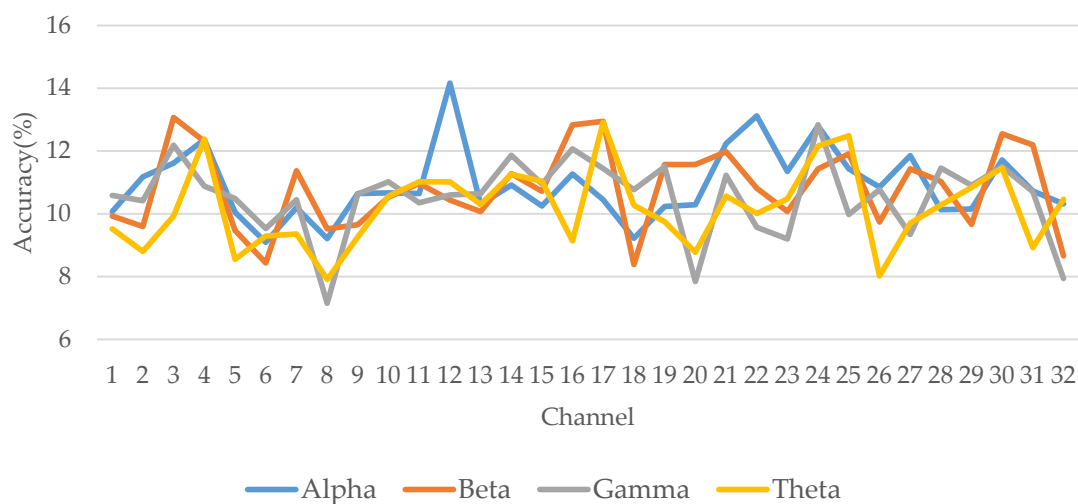
*6.2. Evaluation of EMER Model*

In this section, the evaluation of EMER model is conducted to verify the pattern approach for recognition of EEG-based multidimensional emotions. An optimized SVM method is applied to evaluate this novel approach. Firstly, the emotional valence and arousal values on DEAP dataset are mapped into emotion labels based on EQA method, and 20 emotions are obtained including: "Anger", "Anxiety", "Concentration", "Confidence", "Despair", "Disgust", "Fear", "Gratitude", "Hope", "Insecurity", "Intimacy", "Joy", "Manic", "Pain", "Passion", "Relaxation", "Sadness", "Surprise", "Tired" and "Trust", however, emotion "Shame" is not detected from the DEAP dataset. Secondly, the data size of each emotion is balanced, where each emotion contains 250 EEG signals. Thirdly, 5 PFP features of each signal are calculated according to the EMER model. Lastly, a 10-fold cross validation with 80% training set and 20% testing set is conducted on a grid research optimal SVM method. Moreover, PSD feature is calculated for a comparative experiment. The evaluation result on the feature performance can be seen from the Figure 4.

It can be observed from Figure 4a that, by selecting the PFP features, the prediction accuracy is averagely above 90%, the alpha, beta and gamma bands have the average accuracy about 93.5%, however, theta band reveals an unstable prediction performance, but still, the averagely accuracy is about 92.25%, and channel 20 (F4 electrode) of theta band has detected the highest prediction performance of 93.99%. The result indicts that the PFP features can highly distinguish the differentia of those emotions. However, when dealing with single channel recognition task, it can be observed from Figure 4b that the PSD feature of which only reveals the distribution of power over frequency is not efficient enough to performance the recognition task, the maximum accuracy when applied with PSD is only 14%. Instead, the PFP features reserve more information on the partial

variation in signal, which is differed from the analysis strategy of overall or average feature of each signal.
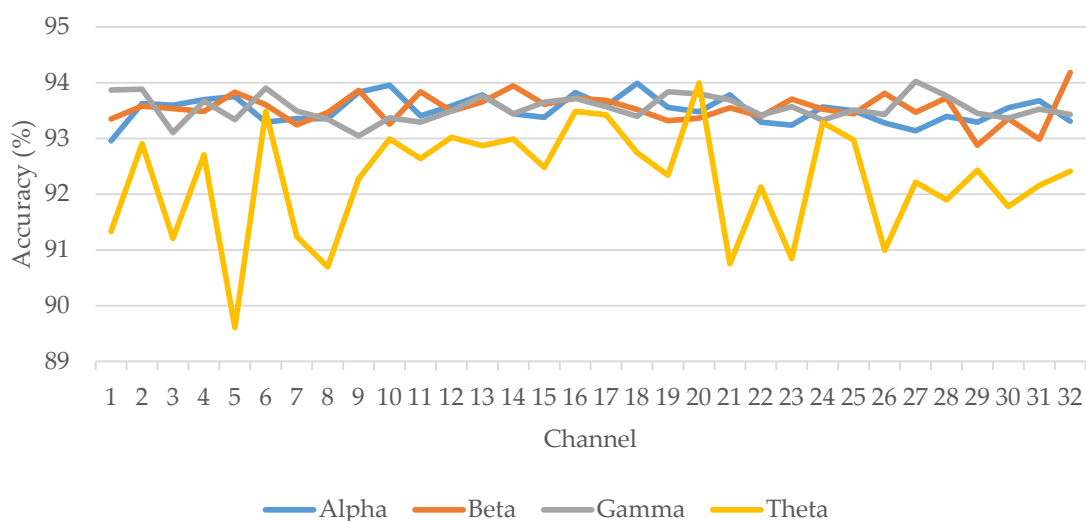


(**a**) Performance on PFP Features



(**b**) Performance on PSD Feature

**Figure 4.** Evaluation on Feature Performance. (**a**) Performance on PFP Features; (**b**) Performance on PSD Feature.

Except for the accuracy, other evaluation indexes on the performance of EMER model are also analyzed as F1-score, Precision and Recall which listed at Table 5. It can be observed that EMER model has separately reached 0.9364 of F1-score, 0.9654 of precision and 0.9317 of recall, which has proved its efficiency.

**Table 5.** Overall Performance of EMER Model.

| F1-Score | Precision | Recall |
|---|---|---|
| 0.9364 | 0.9654 | 0.9317 |

The average prediction accuracy of overall channels and frequency bands on each of emotions is shown at Table 6. It can be observed that the accuracy values of 18 emotions have reached above 90%, and the standard deviation values have revealed that each channel and each frequency band can be efficient on recognizing emotions. The recognition results on "Hope" and "Sadness" might be overfitting due to the original data size of those two emotions are rather a few, however, "Surprise" has the largest data size among 20 emotions of 242 signals are obtained originally, and as a result, the performance on "Surprise" has reached at averagely 96.62%, and the standard deviation is only 2.53.

**Table 6.** The Average Performance on Recognition of 20 Emotions.

| Emotion | Accuracy | Standard Deviation |
|---|---|---|
| Anger | 99.77% | 1.20 |
| Anxiety | 96.56% | 3.96 |
| Concentration | 90.20% | 6.03 |
| Confidence | 99.31% | 1.91 |
| Despair | 99.96% | 0.44 |
| Disgust | 95.99% | 4.05 |
| Fear | 85.48% | 5.95 |
| Gratitude | 99.86% | 1.58 |
| Hope | 100.00% | 0 |
| Insecurity | 99.77% | 1.33 |
| Intimacy | 43.45% | 5.81 |
| Joy | 95.18% | 4.10 |
| Manic | 73.39% | 6.38 |
| Pain | 99.70% | 1.19 |
| Passion | 93.24% | 5.08 |
| Relaxation | 99.15% | 3.07 |
| Sadness | 100.00% | 0 |
| Surprise | 96.62% | 2.53 |
| Tired | 99.55% | 1.56 |
| Trust | 92.09% | 4.99 |
| Anger | 99.77% | 1.20 |

Furthermore, the prediction accuracy values on each single channel and each frequency band of 20 emotions are shown at Figure 5. It can be observed that most emotions have been accurately predicted with accuracy ranges from 80% to 100% with single channel and single band information. Interestingly, intimacy has the lowest prediction rate at averagely 43%, and manic is remained between 60% and 80%. However, from the confusion matrix of "Intimacy", all wrongfully predicted data are classified as "Surprise". The semantically similarity is further analyzed on those emotions, which shows that "Intimacy" and "Surprise" are closely mapped in valence-arousal domains where the distance is only 0.7. As for "Manic", the confusion matrix also shows that a large part of wrongfully predictions are labeled as "Surprise", the distance between "Manic" and "Surprise" is 2.1, which larger than the distance of "Intimacy" and "Surprise" but closer than other emotions. It can be assumed that, those emotions such as "Intimacy" and "Manic" might have overlapped in some parts of signal with "Surprise" especially the emotion "Intimacy".
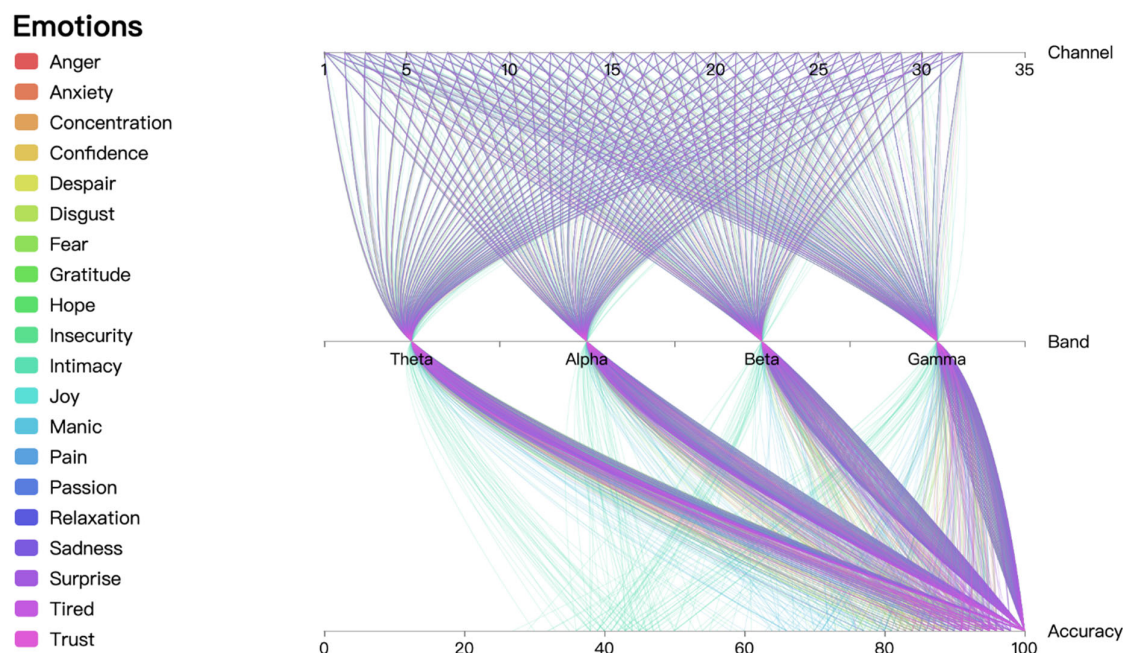
**Figure 5.** Prediction Accuracy of 20 Emotions on Single Channel and Single Frequency Band.

### 6.3. Occurrence of Significant Flutuation Patterns

In this section, the brain activities among different emotions is visualized based on the occurrence of significant fluctuation patterns, which referred to the amount of those fluctuation patterns that only detected on single or similar emotions among the criteria rules set. The matched number of "Representative" and nine subcategorized "Similar" rules is calculated along in the EMER model. The occurrence number of those fluctuation patterns can be more objectively on reflexing the area where more significant brain activities are detected when individuals are experiencing different emotions. A normalization process is conducted for some emotions have been detected with over thousand patterns while some might only have detected with a rather insignificant amount. The visualization of the brain activities based on the occurrence of significant pattern fluctuation pattern under each emotion is shown at Figure 6.
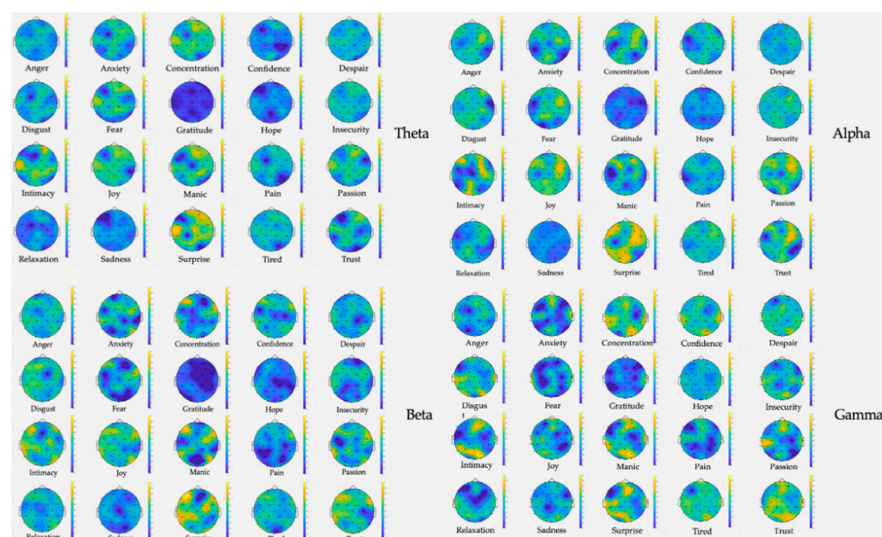


**Figure 6.** 2D Scalp Map of Brain Activities.

From Figure 6, it can be seen that four bands react differently when experiencing different emotions. For example, "Surprise" has detected a significant amount of fluctuation changes in all four frequency bands, especially the right anterior region and left posterior region, the left anterior region is more actively responded in alpha and beta bands. "Intimacy" and "Manic" are also detected high activity in four bands with the similar areas. "Trust" is responded differently in each band, "Gratitude" is extremely inactive both in theta and beta bands. "Hope" is relatively active in gamma band compared to other bands, on the contrary, "Fear" is relatively inactive in gamma band compared to other bands, and "Relaxation" is relatively inactive in theta band compared to other bands.

Some similar emotions groups such as: "Fear", "Anxiety" and "Insecurity"; "Despair" and "Sadness"; "Surprise" and "Intimacy"; "Confidence" and "Trust" are all observed with the slightly different degree of activity but similar brain area in all four bands.

## 7. Discussion

The EMER model performed splendidly on recognition of emotions, this novel approach gives an insight on emotion recognition that the partial fluctuation pattern of EEG signal is suitable on interpreting emotions, when experiencing certain emotion, the EEG signals occurred significant change patterns, which can be more directly on recognizing emotional status. And among the 20 emotion categories, each emotion has detected significant and particular change patterns even for those complex emotions, as for some semantically similar emotions which are regarded as partially overlapped in physiological signal, EMER model can still distinguish them correctly based on PFP features. Moreover, the 4 frequency bands as alpha, beta, gamma and theta have proved its efficiency on recognition emotions when applied with PFP features, which reveals the potential of theta and alpha bands on recognizing emotions.

Also, some interesting phenomena are occurred when distinguishing similar emotions. The prediction results of "Intimacy" and "Manic" which indict that: some basic emotions such as "Surprise" might have a greater range of affection on those similar overlapped complex emotions, for example, for "Manic" when it has a farther distance with "Surprise", the prediction accuracy has increased compared to the prediction accuracy of "Intimacy" which is much closer to "Surprise". Those complex emotions which are acquired by learning, external factors such as morality might have different influence on individuals when cognizing emotions [47], this theory can be also applied to the result of "Gratitude", which is semantically similar with "Confidence" and "Trust", however, inactivity in brain area is observed which is opposite from "Confidence" and "Trust". Another possibility might be data itself that the distribution of the data size under each emotion is uneven, which causes that some emotions have detected less criterial rules for classifying the differentia among similar emotions. For example, "Surprise" has the largest data size compared to other emotions, 242 signals are obtained originally, therefore, more criterial rules are discovered to generate more significant PFP features, as a result, it has reached an average accuracy of 96.62%. Furthermore, the number of criterial rules for "Manic" and "Intimacy" are relatively lesser than "Surprise", the significance of those two emotions might not be fully discovered.

Our proposed approach is to discover the relevance on the fluctuation patterns among EEG signals for emotion recognition task in each frequency bands by using single channel information, which is differed from the general strategies which focused on particularly high frequency bands or optimization of channel selection for recognition of EEG-based emotions. Furtherly, the recognition task is extended into 20 different emotion categories, the differentia of those emotions can be successfully distinguished based on the PFP features. Moreover, the semantically similarity among emotions is proved as physiologically similar among similar emotion groups. However, the limitations in differentiation of similar emotions are mainly due to the overlapping issue occurred

among complex emotions, which is restricted by the data size of each emotion. Therefore, we will continuously collect more EEG signals by our own in our future work for further analysis. Moreover, the external factors that might have an influence on those complex emotions will be taken into consideration.

## 8. Conclusions

In this paper, we proposed a novel pattern approach based on PFP features for recognition of EEG-based multidimensional emotions. The EQA method is proposed to quantify the multidimensional emotional statue, questionnaire and semantic analysis about the correlation between emotions are obtained for objectively reflexing on the correlation between emotions. The EMER model is proposed to discover the criterial rules for recognition of multidimensional emotions, furthermore, the PFP features are extracted to classify the differentia of emotions. Lastly, the evaluation is conducted to verify the pattern approach on emotion recognition, also, the correlation between semantically similar emotions are analyzed. As a result, the novel pattern approach has proved its efficiency on recognition task.

The overall prediction accuracy of all emotions on theta, alpha, beta and gamma bands have all reached above 92%, which proved that not only high frequency bands as beta and gamma are better for recognizing emotions, theta and alpha bands have also performed greatly. Moreover, each electrode of 32 channels has reached a rather steady accuracy, at averagely 93.5%, which indicts that the potential of single channel on recognizing different emotions. Particularly, theta band is outperformed unexpectedly when only based on single EEG channel, the accuracy ranges from 89% to 93%, and except for channel 5 (FC5), the rest channels have reached the accuracy above 90% separately.

The recognition accuracy of 18 emotions have averagely reached above 90%, except for "Intimacy" and "Manic", where the recognition accuracy of "Intimacy" is 43% and 73% for "Manic". The confusion matrixes of those two emotions show that all wrongfully predicted signals are classified as "Surprise", moreover, those three emotions are semantically similar from the valence-arousal domains, which might indicates that the complex emotions as "Intimacy" and "Manic" might be overlapped in a certain extent to the basic emotion "Surprise". Other than those two emotions, our model can classify the rest emotions with a great result.

Semantically similar groups of emotions are proved to appear similar partial fluctuation patterns in the EEG signals. Moreover, for groups such as: "Fear", "Anxiety" and "Insecurity"; "Despair" and "Sadness"; "Surprise", "Intimacy" and "Manic"; "Confidence" and "Trust", similar occurrence pattern of significant fluctuation patterns is observed in similar brain area.

Above all, the EMER model has verified the novel pattern approach for recognition task from EEG signal when based on the PFP features with a high recognition accuracy on each frequency band and each single channel.

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**Data Availability Statement:** Publicly available dataset was analyzed in this study. This data can be found here: [http://www.eecs.qmul.ac.uk/mmv/datasets/deap/].

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