# Pleasure, Arousal, and Dominance Mood Traits Prediction Using Time Series Methods

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## Abstract

Independent mood traits comprise three primary components – pleasure, arousal, and dominance (Mehrabian, 1996). Forecasting these traits is beneficial for several subjects, such as behavioral science, cognitive science, decision making, mood disorders treatment, and virtual character development in artificial intelligence. In this study, an extended model is proposed to predict independent mood components based on the emotion and mood history of 108 individuals with different backgrounds and personalities. Emotion history of all these individuals was recorded hourwise for six days, and their daily mood history obtained. The proposed model consists of various types of statistical forecasting methods, such as Holt-Winter's additive model and seasonal time series model, by integrating current known appraisal theories and aided by mood history probability distribution. The predicted values for the seventh day and the trend of the outcome results reveal that: (1) Pleasure mood trait trend varies significantly between individuals, but it can be considered as predictable; (2) Arousal mood trait is unpredictable for a short time interval; however, it is possible to have close predictions over long time intervals. (3) Dominance mood trait can be predicted for a short time interval, but not for a long time interval. These findings can shed light on the way mood states and behavior of human beings can be predicted.

**Keywords:** mood prediction, emotion forecasting, time series, decision making

During the last few decades, finding a model to describe and predict mood states has played a significant role in many fields of study, such as behavioral science, artificial intelligence, and mood-related disorders studies. Developing such models for predicting mood states can be used to identify possible treatments for mood-related disorders. Therefore, researchers in the field of psychology were mostly interested in using such models for treating disorders such as depression and different types of bipolar mood disorders (Daugherty et al., 2009; Ortiz et al., 2015). In addition, developing a virtual character to be used in a humanoid robot and video games is the other most frequent usage of mood states forecasting models in the field of artificial intelligence and entertainment industries, respectively (Egges et al., 2003; Kazemifard et al., 2006; Gebhard, 2005; Kasap et al., 2009).

The most basic model to describe how objects, agents, and events are appraised based on personalities of individuals was introduced by Ortony, Clore, and Collins (OCC) in the early 1990s (Ortony et al., 1990). The OCC model can be divided into three branches: (1) Appraisal of events to be found pleasant or not with respect to the agent's goals; (2) Actions of the agents to be approved or denied; and (3) Appraisal of liking or disliking objects based on behavior of the agent (Kazemifard et al., 2006). On the other hand, Mehrabian introduced a model based on three almost independent mood traits – Pleasure, Arousal, and Dominance (PAD) – to describe emotion and mood states (Mehrabian, 1996). Again, the ALMA approach was introduced as the combination of the OCC and PAD models by mapping OCC emotions to PAD mood components (Gebhard, 2005). Each mood state has been defined over time by the three PAD mood components, and can be updated by the occurrence of emotion states and previous mood states.

In the proposed approach, these PAD mood traits are updated and forecast based on the OCC, Mehrabian, and ALMA models by using time series forecasting methods, information regarding personality traits, estimated emotion states, and mood history probability distribution of individuals. In this methodology, a mapping from personality traits to PAD space is used to assign the initial mood state for each PAD component (Mehrabian, 1996; Gebhard, 2004), and a proposed formula is applied to update the mood states based on emotion and mood states history (Mehraei & Akcay, 2016). In the forecasting stage, time series methods are used to predict the possible emotion states, and mood states history is applied to assign probabilities to the predicted mood states.

## Methods

### Sampling and Data Collection

The sample in this study consists of 108 volunteers, who are mostly international students or staff at Eastern Mediterranean University. Since these volunteers were born in different countries, they have diverse backgrounds and values. Therefore, it was essential to collect information about their personality type. In this study, OCEAN personality traits – which are Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism (Mehrabian, 1996) – were measured for each individual (Goldberg & Lewis, 1992). Moreover, the most significant emotion that each individual felt hour by hour in his/her awake time for six days was recorded by making the volunteers keep the questionnaire with them for the whole week. The possible emotion states were described to the volunteers carefully before they started filling the questionnaire to make their answers accurate for the study. The initial number of volunteers was 150, but 42 of them were eliminated from the study because there was either some missing data or signs of reluctance on their part in filling the forms. The reliability of their answers was tested by checking whether the trend of their emotional states was random or not. 108 of the initial sample size satisfied the conditions and were selected for being processed.

**Initializing and Updating Mood States**

The initial mood state for each individual was measured by a mapping from OCEAN personality traits into Mehrabian's PAD space (Mehrabian, 1996; Gebhard, 2004). This mapping is defined as following: (1) Pleasure = 0.21*Extraversion + 0.59*Agreeableness + 0.19*Neuroticism, (2) Arousal = 0.15*Openness + 0.3*Agreeableness – 0.57*Neuroticism, and (3) Dominance = 0.25*Openness + 0.17*Conscientiousness + 0.6*Extraversion – 0.32*Agreeableness.

To update mood states, the same proposed formula was applied which was used in the previous study (Mehraei & Akcay, 2016). In this formula, mood states are updated by considering them as a function of previous mood and emotional states. Since changes in emotion states are more sensitive to time compared to mood states, a mood update is applied after the occurrence of 12 emotion states. The formula is as follows: $M_{12t} = W_1 M_{12t-12} + W_2 \phi(e)$, where $\phi(e) = \frac{e_{12t} + e_{12t-1} + \ldots + e_{12t-11}}{12}$, $t$ represents time scale, $M_{12t-12}$ is the previous mood, $\phi(e)$ is the history of previous emotion states, and $W_1$, $W_2$ are coefficients as weights. The values to be assigned as coefficients can be measured based on individual's possible mood swings. For example, we expect patients suffering from bipolar mood disorders or panic disorders to experience mood swings much more than healthy individuals (Bowen et al., 1994). Therefore, the value of the coefficient should be considered bigger in such patients and to have a higher weight for the last 12 emotion states rather than the weight for the previous mood. In the present study, these coefficients are considered as constant coefficients since the volunteers were selected randomly with no record of mental illness.

To measure emotion history function values in the formula, the average of the last 12 emotion states were considered. Each of these emotion states was recorded by using the OCC model to distinguish between possible emotions. ALMA's approach to mapping from the OCC emotions to Mehrabian's PAD independent mood traits is illustrated in Table 1 (Gebhard, 2005).

| Emotions | P | A | D |
|---|---|---|---|
| ADMIRATION | 0.5 | 0.3 | -0.2 |
| ANGER | -0.51 | 0.59 | 0.25 |
| DISLIKING | -0.4 | 0.2 | 0.1 |
| DISAPPOINTMENT | -0.3 | 0.1 | -0.4 |
| DISTRESS | -0.4 | -0.2 | -0.5 |
| FEAR | -0.64 | 0.6 | -0.43 |
| GLOATING | 0.3 | -0.3 | -0.1 |
| GRATIFICATION | 0.6 | 0.5 | 0.4 |
| GRATITUDE | 0.4 | 0.2 | -0.3 |
| HAPPY **FOR?** | 0.4 | 0.2 | 0.2 |
| HATE | -0.6 | 0.6 | 0.3 |
| HOPE | 0.2 | 0.2 | -0.1 |
| JOY | 0.4 | 0.2 | 0.1 |
| LIKING | 0.4 | 0.16 | -0.24 |
| LOVE | 0.3 | 0.1 | 0.2 |
| PITY | -0.4 | -0.2 | -0.5 |
| PRIDE | 0.4 | 0.3 | 0.3 |
| RELIEF | 0.2 | -0.3 | 0.4 |
| REMORSE | -0.3 | 0.1 | -0.6 |
| REPROACH | -0.3 | -0.1 | 0.4 |
| RESENTMENT | -0.2 | -0.3 | -0.2 |
| SATISFACTION | 0.3 | -0.2 | 0.4 |
| SHAME | -0.3 | 0.1 | -0.6 |

Table 1: Mapping from OCC into PAD.

**Forecasting Emotion Traits by Time Series Methods**
Time series analysis is a statistical method to describe, analyze, and predict the behavior of systems based on discrete time dimension. In other words, time series is a recorded data set based on time, and its main application is to predict unknown future data by using observed data. This method has been applied in many fields and topics such as finance and econometrics (Enders, 2004), climate and weather forecasting (Lau & Weng, 1995), and social sciences (McCleary et al., 1980). There are different types of time series methods, and choosing the appropriate one is essential to develop an accurate model.

In our study, emotion states of each individual were recorded based on time, and time series as a forecasting method seemed an appropriate model to predict its possible emotion states. Since pleasure, arousal, and dominance mood traits are considered to be independent of one another (Mehrabian, 1996), time series methods were applied to each one of these components separately. The statistical software package, which has been used to choose between time series various types, is the 20$^{th}$ version of Statistical Package for Social Sciences (SPSS).

**PAD Mood Traits Prediction**
The aim of this study was to predict the possible PAD mood traits of each individual at the end of the week by having information about the individual's personality and his/her emotion states time series data for the first six days.

The possible values for each of PAD components are between -1 and 1. To distinguish between mood states, it is essential to categorize them based on the combination of positive/negative signs for each of these PAD components. These mood groups are illustrated in Table 2 (Mehrabian, 1996).

| | | | |
|---|---|---|---|
| +P +A +D | Exuberant | -P +A +D | Hostile |
| +P +A –D | Dependent | -P +A –D | Anxious |
| +P –A +D | Relaxed | -P –A +D | Disdainful |
| +P –A –D | Docile | -P –A –D | Bored |

Table 2: Mood groups based on PAD traits.

Based on the emotion states time series data, it was possible to predict the trend of each PAD traits by using time series methods. Moreover, it was possible to update mood states based on the proposed formula and assigning them to one of the groups provided in Table 2. However, it has been noticed that for all individuals, there are times when one or some components of PAD mood traits are not predictable. In such cases, it is essential to consider mood history probability distribution of each individual to predict certain unknown PAD traits at the end of the sixth day. If someone does not experience a particular mood state within six days, it does not mean that the person will not experience it during the seventh day. Thus, the probability that such mood states occur in the corresponding mood history probability distribution shouldn't be equal to zero. Therefore, 20 percent of prospects are considered to be the mood states of an individual that he/she did not experience during the previous week.

**Results and Discussion**

The advantage this study has over the previous one (Mehraei & Akcay, 2016) lies in its larger sample size. In the previous study, the way mood states could be predicted by using time series methods was described. However, significant results could not be obtained for the data because it was gathered from only three individuals. In this study, the data are recorded from 108 volunteers and thus offers significant results.

As expected, personality traits of these individuals differed significantly from each other. As soon as the OCEAN personality traits of the individuals were obtained, their initial PAD traits were also measured by the mapping explained in section 2.2. For example, for one of the individuals Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism were found to be 0.65, 0.97, 0.35, 0.60, and 0.45, respectively. Therefore, by using the mentioned mapping from OCEAN personality traits to PAD (Mehrabian, 1996; Gebhard, 2004), the participant's initial pleasure, arousal, and dominance traits were found to be 0.51, 0.02, and 0.34, respectively.

The mapping illustrated in Table 1 made it possible to create time series data for emotion states regarding PAD mood traits. Different types of time series forecasting models were suggested by using SPSS for each mood component of each individual with 95 percent confidence. It has been observed that the trends for pleasure mood component differed significantly from one person to another, but it had a predictable direction for more than 98 percent of individuals. On the other hand, arousal mood component seemed to have different trends compared to the pleasure trait. In this study, the short and long time intervals were considered to be at least one day and a month respectively. By considering the long time interval, arousal trait had either increasing or decreasing trend for more than 90 percent of individuals, but for the remaining individuals, the trend of this component seemed to be random. It has been observed that dominance mood trait is hard to predict over a long time interval. However, it was predictable in a short time interval for more than 87 percent of individuals. Output results for all predictable mood components showed values more than 0.75 as stationary R-squared for the emotion states time series data. Therefore, such results proved that these data are indeed time-dependent, and time series methods are appropriate tools to predict PAD mood traits. The summary of the output results for all 108 individuals is illustrated in Table 3. The possible types of time series methods for these emotion states data were Autoregressive (AR), Moving Average (MA), Seasonal, and Holt-Winter's Additive. The relative frequency percentages for these time series models are shown in Table 3 component-wise. The p-value for testing all of these models was considered to be significant where less than 0.05.

| Type of time series | Pleasure (P) | Arousal (A) | Dominance (D) |
|---|---|---|---|
| AR | 3% | 3% | 1% |
| MA | 68% | 2% | 28% |
| Seasonal | 26% | 42% | 56% |
| Holt-Winter's Additive | 1% | 43% | 2% |
| Random data | 2% | 10% | 13% |

Table 3: Relative frequencies of appropriate time series models for PAD components.

To overcome the randomness problem which was observed in particular PAD mood components of some individuals, mood history probability distribution was helpful. The updated mood states for each day were calculated as explained in section 2.2. Occurrence frequencies for each mood states from Table 2 were calculated after checking all updated mood states. Finally, the relative frequency of each mood group was considered as probabilities. As explained in section 2.4, relative frequencies were corrected by assigning 20 percent probability to those mood groups with zero frequencies, and 80 percent to those with frequencies more than one.

It was possible to predict all PAD components for some individuals based on their emotion states time series data. Therefore, their mood states could be updated easily from the proposed formula in section 2.2 and could be predicted by assigning predicted signs to PAD components and choosing the corresponding mood group from Table 2. On the other hand, one or more PAD components were not predictable for some individuals. For example, pleasure and dominance were predictable for one individual, and it was clear that this person's corresponding signs will be positive at the end of the week. To predict the arousal component, the person's mood history probability distribution can be helpful. As an example, the probability distribution for mood history of this person is demonstrated in Table 4. Therefore, in the case of negative or positive arousal, the person's mood group will be bored or anxious by 0.32 and 0.68 probability by considering Tables 2 and 4. Such predictions had 95 percent confidence because the p-values considered in all the time series forecasting methods were less than 0.05.

| Mood traits | Frequency | Probability |
|---|---|---|
| Exuberant | 1 | 0.11 |
| Dependent | 2 | 0.23 |
| Relaxed | 1 | 0.11 |
| Docile | 0 | 0.07 |
| Hostile | 1 | 0.11 |
| Anxious | 2 | 0.23 |
| Disdainful | 0 | 0.07 |
| Bored | 0 | 0.07 |

Table 4: Mood history probability distribution for a random individual from the sample.

**Conclusion**

The proposed prediction models were applied to 108 individuals. The data related to their personality and emotion history were obtained, and their mood states were updated daily. PAD traits for each individual were predicted with 95 percent confidence level and compared with their actual PAD traits at the end of the week. The comparison of updated mood states based on recorded actual data with time series predictions revealed that more than 86 percent of predictions regarding the mood group were correct. Therefore, it is demonstrated that time series methods are appropriate approaches to predict PAD components. The obtained results validate Alma's approach (Gebhard, 2005) and our previous work (Mehraei & Akcay, 2016). As a future work, Stochastic Hybrid Petri Nets (SHPNs) can be used as a mathematical modeling tool to improve the accuracy of PAD traits predictions.

Interesting observations were made when the trends of PAD traits in these 108 individuals were compared. The results showed that trends of each PAD components were different from one person to another. However, there were some meaningful conclusions when PAD traits were considered separately as they are independent of each other. Pleasure mood trait has various trends, but these trends are predictable. On the other hand, arousal trait is harder to predict in a short time interval, but it is easier to predict whether it would have a positive or negative sign in a long time interval because its trend has either increasing or decreasing trend in a long time interval in most of the individuals. However, dominance trait is very difficult to predict for a long time interval, but it is predictable for most of the people in a short time interval. These results show that mood predictions should be made componentwise by forecasting PAD traits. In future studies, SHPNs can be used to model these independent mood traits separately to find potential treatments for mood related disorders, such as depression and different types of bipolar disorders. Identifying such potential treatments will be possible by targeting various components and manipulating process rates in the proposed SHPN model.

## References

Bowen, R. C., South, M., & Hawkes, J. (1994). Mood swings in patients with panic disorder. *The Canadian Journal of Psychiatry, 39*(2), 91–94. https://doi.org/10.1177/070674379403900205

Daugherty, D., Roque-Urrea, T., Urrea-Roque, J., Troyer, J., Wirkus, S., & Porter, M. A. (2009). Mathematical models of bipolar disorder. *Communications in Nonlinear Science and Numerical Simulation*, *14*(7), 2897–2908. https://doi.org/10.1016/j.cnsns.2008.10.027

Egges, A., Kshirsagar, S., & Magnenat-Thalmann, N. (2003, September). A model for personality and emotion simulation. In *International Conference on Knowledge-Based and Intelligent Information and Engineering Systems* (pp. 453–461). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-45224-9_63

Enders, W. (2004). Applied Econometric Time Series, by Walter. *Technometrics*, *46*(2), 264. https://doi.org/10.1198/tech.2004.s813

Gebhard, P. (2005, July). ALMA: a layered model of affect. In *Proceedings of the Fourth International Joint Conference on Autonomous Agents and Multiagent Systems* (pp. 29–36). ACM. https://doi.org/10.1145/1082473.1082478

Goldberg, L. R. (1992). The development of markers for the Big-Five factor structure. *Psychological Assessment*, *4*(1), 26. https://doi.org/10.1037/1040-3590.4.1.26

Kasap, Z., Moussa, M. B., Chaudhuri, P., & Magnenat-Thalmann, N. (2009). Making them remember – Emotional virtual characters with memory. *IEEE Computer Graphics and Applications*, *29*(2), 20–29. https://doi.org/10.1109/MCG.2009.26

Kazemifard, M., Ghasem-Aghaee, N., & Oren, T. I. (2006). An event-based implementation of emotional agents. *Simulation Series*, *38*(4), 63.

Lau, K. M., & Weng, H. (1995). Climate signal detection using wavelet transform: How to make a time series sing. *Bulletin of the American Meteorological Society*, *76*(12), 2391–2402. https://doi.org/10.1175/1520-0477(1995)076<2391:CSDUWT>2.0.CO;2

McCleary, R., Hay, R. A., Meidinger, E. E., & McDowall, D. (1980). *Applied time series analysis for the social sciences*. Beverly Hills, CA: Sage Publications.

Mehrabian, A. (1996). Analysis of the Big Five Personality Factors in terms of the PAD Temperament Model. *Australian Journal of Psychology*, *48*(2), 86–92. https://doi.org/10.1080/00049539608259510

Mehrabian, A. (1996). Pleasure-arousal-dominance: A general framework for describing and measuring individual differences in temperament. *Current Psychology*, *14*(4), 261–292. https://doi.org/10.1007/bf02686918

Mehraei, M. & Akcay, N. I. (2016). Mood and emotional states prediction by times series methods, *International Psychological Applications Conference and Trends (INPACT 2016)*, Pracana C. & Wang, M. (eds), Lisbon, Portugal, 382–386.

Ortiz, A., Bradler, K., Garnham, J., Slaney, C., & Alda, M. (2015). Nonlinear dynamics of mood regulation in bipolar disorder. *Bipolar disorders*, *17*(2), 139–149. https://doi.org/10.1111/bdi.12246

Ortony, A., Clore, G. L., & Collins, A. (1990). *The cognitive structure of emotions*. Cambridge University Press.

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