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# Temporal dynamics of EEG during anesthesia

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***Abstract*—The study of electrical brain activity (EEG) during anesthesia has received much attention over recent years. This can be attributed to the fact that such study has vast clinical and research implications. In this work we study how the linear temporal dynamics of EEG activity are affected by the administration of anesthetic agents. The measure of lagged auto-correlation (LAC) is applied to the EEG activity of 10 patients undergoing routine surgery and the evolution of the LAC features is tracked during transitions between wakefulness / unconsciousness. We report a reversible and widespread increase in LAC during anesthesia, with decreased variability compared to wakefulness. This corresponds to a less complex EEG activity during anesthesia as a result of anesthetic administration and suggests the future utilization of LAC as a feature for discriminating between wakefulness and anesthesia.**

***Index Terms*—electroencephalogram, temporal dynamics, lagged auto-correlation, anesthesia, awareness.**

## I. INTRODUCTION

Monitoring the electrical brain activity (electroencephalogram, EEG) during anesthesia has received great attention in the recent years. Modern anesthesia involves the administration of different drugs to achieve the desired components of unconsciousness, amnesia, analgesia and immobility [1]. The multi-component nature of anesthesia complicates the work of anesthetists, who rely on experience and broad guidelines for administering this chemical cocktail to the patients. As a result, the phenomenon of awareness during anesthesia could arise from incorrect dosage of anesthetics, or other factors, such as equipment failure [2]. Awareness could be prevented via the use of specialized equipment that monitors the depth of hypnosis.

The anesthetic-induced measurable changes in the EEG activity can provide indications as to the patient state of hypnosis during surgery. Thus, the EEG has come to be an important tool in clinical applications and commercially available monitors, such as the BIS [3], are being introduced for routine patient monitoring during surgery. At the simplest level these monitors use the loss of high frequencies and shift to low frequencies observed during anesthesia as a measure of anesthetic drug action. Given that current monitoring methods suffer from robustness issues (e.g. see [4]), the need for more precise, simpler and physiologically-based methods has never been higher.

In addition to the methods utlized in monitoring devices a number of other methods have been applied to study the anesthetic-induced EEG changes. The applied methods look at different properties of the EEG signals, such as its time-frequency content, its complexity and its information-based content (for some examples see [5]–[9] and references within). In this work we investigate whether information contained in the temporal dynamics of EEG activity could provide necessary and sufficient information to discriminate between wakefulness and anesthesia. A related study by Julitta et al. investigates the use of non-linear temporal dynamics, measured through mutual information, of the frontal EEG activity (3 electrodes) as a measure of anesthetic depth [10]. Here, we study whether such information can be extracted with *linear* methods instead. That is, we study how the administration of anesthetics affects the linear temporal dynamics of the EEG activity as measured through lagged auto-correlation (LAC). If LAC features successfully capture changes between wakefulness / anesthesia, then this is advantageous over the more complex method of mutual information, whose accurate estimation requires large data segments and depends on estimating the underlying probability distribution. More specifically, in this work the lagged auto-correlation is estimated from whole-head EEG data obtained from 10 patients during surgery and the evolution of the LAC features during wakefulness and anesthesia is monitored.

## II. METHODS

### A. Dataset

The data has been collected as part of a larger study at Nicosia General Hospital, Cyprus. The study was approved by the Cyprus National Bioethics Committee and patients gave written and informed consent for their participation. A detailed description of the dataset can be found in our previous studies (see, for example, [9]). In this preliminary study we re-analyzed a small subset of the data from 10 patients with mean age (± standard deviation) 38.7 (± 19.0) who underwent routine general surgery. Anesthesia was induced by the on-duty anesthetist with a propofol bolus (2-4 mg/kg) and maintenance was achieved via continuous intravenous administration of propofol. During surgery other agents, such as neuromuscular blocking agents and analgesic drugs, were administered as per surgery requirements. EEG data collection was performed with the TruScan32 (Deymed Diagnostic, CZ) using the 10/20 system. Data were sampled at 256 Hz.

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### *B. Methodology*

The evolution of the EEG temporal dynamics was performed with lagged auto-correlation (LAC). Given a time series, $X = [x(1), x(2), ..., x(T)]$, LAC provides a quantitative measure of the dependence of current observations of $X$ on its past observations at a time lag $\tau$:

$$LAC(X, \tau) = C(x(1, ..., T - \tau), x(\tau, ..., T)) \qquad (1)$$

C is the correlation,

$$C(X_1, X_2) = \frac{E[(x_1 - \mu_{x_1})(x_2 - \mu_{x_2})]}{\sigma_{x_1}\sigma_{x_2}} \qquad (2)$$

where $\mu$ is the mean and $\sigma$ is the variance.

Before estimating the LAC features some necessary preprocessing steps were performed. Firstly, the EEG data were filtered with a 50-Hz Notch filter (function '*iirnotch*' in Matlab$^{®}$). This ensured that any line noise contamination present in the data was removed, as this could have induced spurious correlations during estimation of the LAC features. Secondly, the outlier LAC values that corresponded to EEG windows contaminated with diathermy artifacts were removed from further analysis. Since diathermy causes sharp drops in the LAC features during anesthesia (see fig. 1 for an example), the removal of the outlier values was achieved by applying a simple threshold function. Thus, any LAC values that fall below this threshold during anesthesia are removed from subsequent analysis. The threshold function was empirically set to 0.95 after visual inspection of the LAC values.

The choice of the delay for estimating the LAC values was performed after trial and error. The LAC was obtained for delays $\tau = 1, 5, 10, 20, 30, 50, 70, 100$ and after visually inspecting the resulting LAC features, the delay of $\tau = 1$ was chosen, as this provided a larger and clearer difference between the two conditions of wakefulness and anesthesia.

In summary, the proposed methodology consists of the following steps:

1) Apply a 50-Hz Notch filter to the EEG data to ensure no spurious correlations arise due to line noise.
2) Segment the continuous EEG data into 4-s windows (1024 samples) with 75% overlap (sliding window by 1 s, i.e. 256 samples).
3) For each patient and available electrode, estimate the LAC over all available windows and a time lag $= 1$ sample (4 ms).
4) Apply a threshold to the LAC values during anesthesia to remove outlier values caused by diathermy contamination of the EEG signals.
5) For each patient and electrode estimate the mean LAC and its standard deviation during wakefulness and anesthesia.

## III. RESULTS AND DISCUSSION

The effect of anesthetic administration on the temporal dynamics was studied with lagged auto-correlation (LAC). Figure 1 shows a representative example of LAC features estimated throughout the entire surgical duration for patient S1 and electrode F7. Table I summarizes the general trend of changes in the LAC values observed during wakefulness and anesthesia for all electrodes. The estimated means indicate a widespread increase in LAC during anesthesia. Despite the widespread nature of this increase, this is more prominent in more anterior and central areas compared to posterior areas, which display larger LAC values during wakefulness. This could have implications in a potential utilization of LAC features for discriminating between wakefulness and anesthesia regarding the placement of appropriate electrodes. Table I suggests that electrodes in more anterior positions could provide an increased ability of discrimination due to the larger changes in the measured LAC values.

Figure 2 shows an overview of the LAC values estimated during wakefulness and anesthesia as measured by the standard deviation of the LAC values. Despite the large inter-subject variability in the actual LAC values, all subjects exhibit the same trend: during anesthesia the EEG signal becomes less complex and more predictable, as indicated by the small variance of the estimated LAC values. All differences in the variances of the LAC features for wakefulness and anesthesia are statistically significant (Levene's test, $\alpha = 0.01$).

The increase in LAC during anesthesia implies that anesthetics affect the complexity of EEG activity. The lower and highly variable LAC values observed during wakefulness are replaced by larger and less variable values during anesthesia. In addition, the LAC values display smaller variation during anesthesia than wakefulness. This constitutes the variance (or standard deviation) of the LAC values as a prime candidate feature for discrimination between the two conditions.

The implication of the above observations is that anesthetic administration causes an increase in the similarity of the EEG signal, which is more prominent during short delays (here 1 sample, which corresponds to 4ms). This agrees with evidence in the literature concerning the changes in EEG complexity during anesthesia (e.g. [3, 4]). Evidence from recent imaging studies with isoflurane and halothane [5], sevoflurane [6], midazolam [7] and propofol [8] support a functional disconnection of the cortex from outside sensory experience. This disruption of sensory information flow to the cortex implies that no external input can reach the cortex, resulting to a hypersynchrony of neuronal activity. Consequently, the similarity of EEG activity increases, while its complexity decreases. This justifies the observed increase in LAC values during anesthesia, as these imply an increase in EEG predictability.

The LAC features provide a simple and intuitive way of monitoring patient state of hypnosis during surgery. The information obtained from such features is sufficient such that no non-linear methods, e.g. mutual information, are necessary. Utilization of such features in a monitoring device could include estimation of the LAC features and their variance over a moving window and discrimination between wakefulness / anesthesia using an adaptive threshold. For practical reasons only the minimum number of electrodes at optimum positions

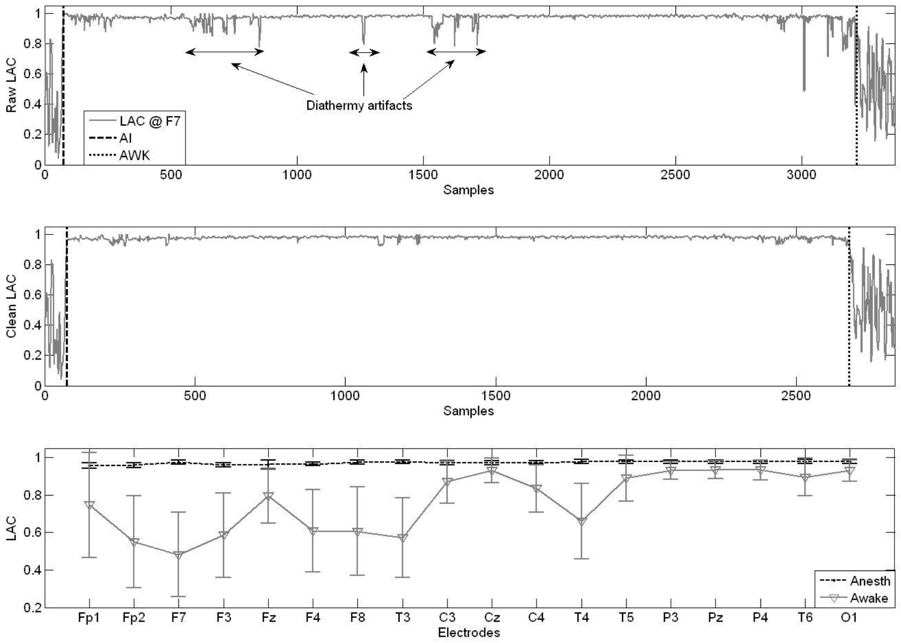

Fig. 1. Top: Raw LAC values for patient S1 at electrode F7. Vertical lines indicate anesthetic administration for induction (dashed line) and recovery of consciousness (dotted line). The effect of diathermy contamination on the LAC values is visible as a sharp decrease in the LAC values during anesthesia. Middle: LAC after removal of outlier LAC values due to diathermy. Bottom: Mean LAC values estimated during wakefulness and anesthesia for patient S1 and all available electrodes (electrode O2 was not available), plotted together with errorbars ( 1 standard deviation).

would be utilized. Figure 2 indicates that it is possible to discriminate between the two states using even a single electrode, with electrodes at fronto-central locations displaying a larger difference of variance for the two conditions. Online discrimination could be achieved via an adaptive threshold, updated based on the estimated variances from previous windows. Such a threshold would track the changes in variance as the patient transitions between the two states. Rather than converting the LAC features to a number from 0-100, the adaptive threshold and the estimated LAC features would be displayed to the anesthetist. This takes into account the inter-subject variability of the LAC features as the anesthetist would be interpreting the LAC patterns directly rather than rely on interpretation of a general, dimensionless and subject-independent number.

## IV. CONCLUSION

We investigate the evolution of the linear temporal dynamics, as measured through lagged auto-correlation (LAC), of the EEG during wakefulness and anesthesia. Our findings confirm that the EEG shifts from more complex patterns observed during wakefulness to less complex and more predictable patterns during anesthesia. The variability of the LAC is also significantly smaller during anesthesia. The LAC features are good candidates for utilization in a future clinical device for monitoring patient state of hypnosis during anesthesia.

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TABLE I
MEAN AND STANDARD DEVIATION OF SUBJECT-WISE LAC AT EACH ELECTRODE

| | Awake | | Anesth | |
|---|---|---|---|---|
| **Electrodes** | ***Mean*** | ***Stand. Dev.*** | ***Mean*** | ***Stand. Dev.*** |
| Fp1 | 0.8459 | 0.1002 | 0.9718 | 0.0052 |
| Fp2 | 0.8505 | 0.1141 | 0.9735 | 0.0076 |
| F7 | 0.7753 | 0.1376 | 0.9732 | 0.0043 |
| F3 | 0.8134 | 0.1286 | 0.9675 | 0.0035 |
| Fz | 0.8892 | 0.0999 | 0.9701 | 0.0063 |
| F4 | 0.8071 | 0.1213 | 0.9686 | 0.0032 |
| F8 | 0.7610 | 0.1298 | 0.9729 | 0.0043 |
| T3 | 0.7284 | 0.1421 | 0.9751 | 0.0046 |
| C3 | 0.8580 | 0.0864 | 0.9732 | 0.0035 |
| Cz | 0.9246 | 0.0395 | 0.9741 | 0.0041 |
| C4 | 0.8767 | 0.0755 | 0.9742 | 0.0040 |
| T4 | 0.7783 | 0.1212 | 0.9754 | 0.0044 |
| T5 | 0.8759 | 0.0691 | 0.9770 | 0.0042 |
| P3 | 0.8968 | 0.0555 | 0.9755 | 0.0044 |
| Pz | 0.9290 | 0.0423 | 0.9762 | 0.0041 |
| P4 | 0.9240 | 0.0414 | 0.9763 | 0.0041 |
| T6 | 0.9019 | 0.0474 | 0.9763 | 0.0044 |
| O1 | 0.9288 | 0.0357 | 0.9766 | 0.0042 |
| O2 | 0.9321 | 0.0376 | 0.9764 | 0.0043 |

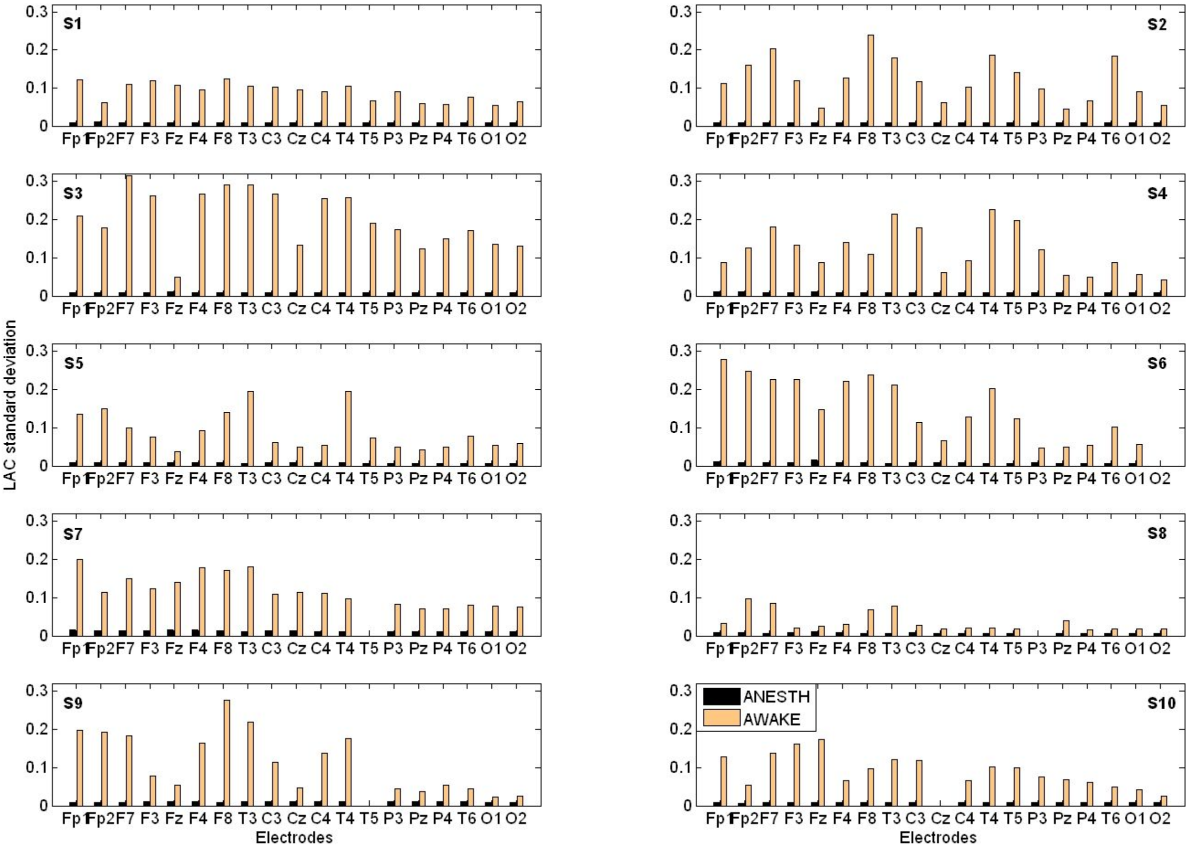

Fig. 2. Standard deviation of LAC features during wakefulness (light) and anesthesia (dark) for each of the 10 subjects studied (S1-S10).

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