RARE SEGMENTS IN TEMPORAL SIGNALS
AND VIDEO RECORDINGS

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Abstract

We can regard temporal record of bio-electrical signal and video as a geometrical object with one more dimension taking into account the temporal evolution of the signal. In this case the video can be regarded as a three dimensional object while the temporal recording of an electrical signal can be regarded as one dimensional geometrical object. One interesting practical and theoretical problem is to find the parts of these figures that differ significantly from all the common parts of the recordings. The deterministic approach for the location of the unusual parts inside the signals and recordings is not feasible, as it needs an exhaustive search in all the parametric space.

In this paper we show that by using a modification of our previously developed probabilistic method to find the most unusual part of a 3D digital image, we can find the temporal intervals and areas of interest of the signals/video and mark the corresponding objects that behave in an unusual way.

Due to the different dynamics along the temporal and the spatial axes, namely the prevalence of the cylinder-like objects in the video and the pseudo-periodic slowly changing spectral characteristics of the bio-electrical signals, an additional step is needed to treat the temporal axis.
1 Introduction

With the increased availability of the bio-electric and simultaneous video recording in hospitals the problem of their automatic processing arises. Although there exist many algorithms to extract the information from a record of one modality, integral systems that observe simultaneously a set of different measurements are rare. The records are frequently processed by high-skilled personnel who habitually are not available 24 hours a day. In the ICU, the detection of seizure, when there are no obvious manifestations of the crisis, is a serious problem that with a proper solution could save many lives.

The goal of the current method is to detect all temporal interval and spatial segments of some spectre of human signals that are not similar to the rest of the recording and eventually could make them available to skilled personnel and/or raise automatic alarm.

Let us regard the video as a 3D geometric figure stacking the frames on top of each other. The goal of the algorithm is to find 3D objects $V^S(t, x, y)$ with shape $x, y \in S$ that are rare in the sense that the distance between $V^S(t, x, y)$ and any other translated object $V^S(t + t', x + x', y + y')$ is the largest or close to the largest possible. The exact solution of this problem is computationally hard, because it requires comparison between the translated objects. Therefore, we follow our previous method designed to solve probabilistically that problem. We give a summary of the methods in the following paragraphs.

As we have stated previously [1, 2], we need, first of all, a mathematical definition of the term “most unusual part”. To do this, we choose some shape $S$ within the image $A$, that could contain that part and we denote the cut of the figure $A$ with shape $S$ and origin $\vec{r}$ by $B^S(\vec{r})$, i.e.

$$B^S(\vec{r}) = S(\vec{r})A(\vec{r} + \vec{r}),$$

where $\vec{r}$ is the in-shape coordinate vector, $\vec{r}$ is the origin of the cut $B_S$ and $S(.)$ is the characteristic function of the shape $S$. Further in this paper we will omit the arguments of $B_S$ when not necessary. We can suppose that the most unusual part is the one that has the largest distance with the rest of the cuts with the same shape. Strictly mathematically, we can suppose that the most unusual part is located at the point $\vec{r}$, defined by:

$$\vec{r} = \arg \max_{\vec{r}} \min_{\vec{r}':|\vec{r}' - \vec{r}| > diam(S)} ||B^{S}(\vec{r}) - B^{S}(\vec{r}')||. \quad (1)$$

Here we assume that the shifts do not cross the border of the image and we do not allow the shapes located at $\vec{r}'$ and $\vec{r}$ to intersect, avoiding this by the restriction on $\vec{r}' : |\vec{r}' - \vec{r}| > diam(S)$.

2 The Method

The minima estimation of Eq. (1) is complicated because the blocks are multidimensional. However, one can simplify it by projecting the blocks $B \equiv B^S(\vec{r})$ and $B_1 \equiv B^S(\vec{r}_1)$ in one dimension using some projection operator $X$. For this aim, we consider the following quantity:
\[ b = |X.B_1 - X.B| = |X.(B_1 - B)|, \quad |X| = 1. \quad (2) \]

The dot product in the above equation is the sum over all \( \rho \)-s:

\[ X.B \equiv \sum_{\vec{\rho}} X(\vec{\rho})B(\vec{\rho}; \vec{r}). \quad (3) \]

If \( X \) is random, and uniformly distributed on the sphere of the corresponding dimension, then the mean value of \( b \) is proportional to \( |B_1 - B| \); \( \langle b \rangle = c|B_1 - B| \) and the coefficient \( c \) depends only on the number of points of the block that can be treated as being its dimensionality, considering the projection operator. However, when the size of the block, e.g. its dimensionality increases, the two random vectors \((B_1 - B)\) and \(X\) are close to orthogonal and the typical projection is small. If some block is far away from all the other blocks, then with some probability, the projection will be large.

We will regard only projections orthogonal to the vector with components proportional to \( X_0(\rho) = 1, \forall \rho \). The projection on the direction of \( X_0 \) is proportional to the mean brightness of the area and thus can be considered as not so important characteristics of the image.

Mathematically the projections orthogonal to \( X_0 \) have the property \( \sum_{\vec{\rho}} X(\vec{\rho}) = 0 \). The distribution of the values of the projections satisfying this property is well known and universal [3] for the 2D natural images and video cuts. The same distribution seems to be valid for a vast majority of the images.

Further, we quantize the projections. If \( B(r) \) and \( B(r') \) have similar projections, then they will belong to one and the same or to adjacent bins. As a first approximation, we can just consider the projections and score the points according to the bin they belong to. The distribution can be described by only one parameter that, for convenience, can be chosen to be the standard deviation \( \sigma_X \) of the distribution of \( X.B \).

The notion of “large value of the projection” will be different for different projections but will always be proportional to the standard deviation. Therefore we can define a parameter \( a \) and score the blocks with \( |X.B| > a\sigma_X \).

Based on the above scheme, in order to find the most unusual blocks of shape \( S \) in an image \( A \), we propose the following algorithm:

0. Initialize: Construct a figure \( B \) with the same shape as \( A \) and with all pixels equal to zero. The result of the algorithm will be saved in \( B \).
1. Generate a random projection operator \( X \) by a carrier with shape \( S \), zero mean and norm one.
2. Project all blocks (convolute the figure). We denote the resulting figure as \( C \).
3. Calculate the standard derivation \( \sigma_X \) of the result of the convolution.
4. For all points of \( C \) with absolute values greater than \( a\sigma_X \), increment the corresponding pixel in \( B \).
Repeat steps 1 to 4 for $M$ number of times.

5. Select the maximal values of $B$ as the most singular part of the image.

2.1 Video Signal

Let us first consider the video signal. First of all the video is simply a video recording of the patient in two plans. It is not a medical image in the sense of the X-Ray and the magnetic resonance image.

We are trying to extract the most unusual parts of the video. The first attempt would be to regard the video as a stack of two dimensional images and use the algorithm described in [2] as it is. Unfortunately this approach does not work. There are at least three problems.

The first is that the objects in the video are more or less constant and therefore they form in the so constructed 3D image elongated cylinders with finite dimensions along the spatial axes and very long extensions along the time axis. The size of the area we choose ought to be larger than the size of the objects we detect and this requirement cannot be fulfilled in the temporal direction.

The second problem is rather specific for the type of video we use. Namely, the infrared camera is very noisy in the absence of artificial light source. This gives a speckle noise comparable with the signal. The high frequency temporal component will actually mask off the signal.

The third problem is the scan frequency of the images. Having some 24-30 frames per second we need to process a huge amount of information in near real time mode. Therefore, even if the method could be theoretically feasible, in practice it will not work because of the lack of productivity – in a typical ICU we have about 40 patients each one with his own video. One will need almost the full power of a modern PC in order to process even few of the video signals.

These three problems make the method of random projections not useful in its original form.

We need to modify the method in order to obtain: (1) limited objects in the temporal dimension, (2) lack of high frequency noise and (3) a reduced temporal data flow. As will be shown below, we can actually achieve the three objectives using a single technique.

In the video records we consider the objects that move to be the parts of the patient’s body. They do not move constantly. There are some limited time intervals in which the objects move. We can extract only the parts of the frames that are not constant and consider only these parts. Representing this as a 3D stack of frames, the duration of the movement is limited and therefore the non-constant parts have a limited size in the time dimension. However, the analysis of the scene, the segmentation and the extraction of moving areas cannot be performed very fast. A much easier technique that can be applied is to filter each pixel value using some high-pass filter along the time axis.

Analogously the high frequency speckle noise, due to the poor light conditions, can be filtered by low pass filter, which combined with the previous one can be implemented as band-pass filter. In this way we have the signal filtered with a frequency spectrum between say $F_0$ and $F_1$. According
to the Nyquist theorem, if the signal is limited within the band \([F_0, F_1]\), we can sub-sample it with no loss of information for any frequency above \(2|F_1 - F_0|\). Thus for 3 Hz bands we can sub-sample the signal with 6 Hz, which drops the frame rate of 24 fps video four times.

If we are interested particularly in epileptic and non-epileptic seizures, we can use the fact that most of the movements during the ictus are temblor movements with a typical frequency of 3-5 Hz.

### 2.2 One Dimensional Signals

Something similar occurs with the one-dimensional bio-electrical signals. In this case it is the temporal development of the signal we are particular interested in. However, because of the nature of the bio-electrical activity we consider (EEG, Electrocardiogram (ECG), Electromyogram (EMG)), the spectrum of the signals is slowly changing in time, with exception to the artifacts and the temporal patterns (spikes, spindles, K-waves) in the signals.

Surprisingly the video and the one-dimensional signal processing seem very similar. At the first stage we filter all signals and the video in 3 Hz bands, then sub-sample the signal above the Nyquist frequency and finally process the results using the algorithm described in [2].

There are many methods that are suitable for analyzing EEG signals, (see [4] and the citations therein). Practically all procedures described in the literature concern the detection of specific events in the signal, building a model for these events. The method we describe in this paper, on the contrary, searches for the parts of the signal that are unusual compared to the rest of the signal. Similar approach, applicable only to 1D signals, is presented in [5]. The random projections are used as a tool to find nearest neighbors in [6].

### 3 Results

We used records of the sleep unit given by a public domain source [7, 8].
Figure 2: Events extracted only from EEG data ($a = 3, M = 1$). The main features are well detected even with only one projection.

3.1 Data Processing

It was observed that there were two types of bio-electrical signals. On one side, the periodic signals as ECG and similar, that are produced as a result of the activity of some autonomous system. The histogram of the projection density of a typical signal of that type is shown in Fig. 1 (left). One can observe a typical Gaussian density. Because of a rapid fall of the tail in that case, it is relatively difficult to use these signals with the method described.

The second type of signal is produced by the non-periodic complex system. As an example, a single channel EEG projection is shown in Fig. 1(right). In this article we used only this type of signal.

We used 10 random projection matrices. The use of 30 random projection matrices, as in the case of 3D medical images, did not give significant advantages. This is probably due to the rejection of the very low frequencies and the fact that we used one dimensional band limited signals. For these signals the standard deviation is smaller than for the case of video.

3.2 Experimental Results and Interpretation

We analyzed the following cases:

A. Extracting the intervals with unusual events only from the one dimensional signals (principally EEG).

In this case we have also used the data from the collection of epilepsy studies [9], and the epileptic records were detected with 99% probability (only one case was not detected) with one false alarm (artifacts in the record). Having in mind that the detector was not specifically designed to detect epilepsy, the results seem very good. However, although the data set [9] is good to compare different methods for epilepsy detection, we do not consider the results representative, because the records are pre-selected not to contain artifact and more important, they are post-selected regarding the results of the surgery – if the results were poor, the corresponding records were not included in the collection. Both conditions are artificial and not realistic in the medical practice.

The result is shown in Fig. 2. After an inspection by a human specialist and annotating the EEG using different EEG records we can observe that the intervals marked as “unusual” by the algorithm are the epileptic seizures, the short arousals and artifacts produced by electrode
problems, the snoring, the REM and the phase II morphological elements (K-complex, spindles) when they occupy more than 30% of the 10 seconds interval.

Changing the parameter $a$ of the algorithm we can select the level of sensitivity of the system. With $a = 4$ only the first two categories are detected. With $a = 3$ all 5 categories are detected.

B. Extracting intervals and areas that correspond to unusual events from the video recording only.

Evidently, the unusual events during the sleep or unconscious state are the movements of the person. In this sense if one is really interested in the events, the technique detects all significant movements of the parts of the body (hands, legs, head) with virtually 100% precision. The best detected is the motor reaction of the epileptic seizure, detectable at level $a = 4$. For $a = 3$ all significant limb and corporal movements can be detected.

C. Mixed use of the EEG and video records.

The main problem is to give a relative weight to the projections corresponding to the video and to the bio-electrical records, respectively. We choose equal weight for all EEG signals and the video. The resulting system can be tuned to capture any epileptoform motion and brain activity even when problems with the electrodes are presented or there is no apparent movement (Fig.3). The system has absolutely no a priori knowledge of what could be regarded as “normal” and what is “abnormal” activity. Therefore detecting seizure periods, REM activity and snoring can be considered as a very good result.

4 Discussion

We presented a method that finds unusual intervals and areas in mixed one dimensional signals and video recording. It is probabilistic and uses random projections in order to represent the signal. The temporal evolution of the signal must be treated differently from the spatial one, due to the different dynamics involved. Namely, all signals ought to be filtered in narrow frequency bands. This is a significant change with respect to the algorithm for 3D images, because it is not previously clear that the band-limited projections can extract the unusual parts of the signal. The probability of error can be adjusted easily by the number of the projections and falls, at
least exponentially, with that number.

Without having any knowledge about the different EEG events and human sleep development, the method extracts most of the important events deserving consideration. The analysis approximates the human specialist performance and therefore, although the results are preliminary, they seem rather promising. The method can be used to present to the neurologist only the parts detected as unusual. Another possible application of the method is to add an automatic analysis on the extracted parts and to produce an alarm in the case of live treating conditions in ICU.

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