USING KOHONEN SELF ORGANISING FEATURE MAPS FOR THE ANALYSIS OF AMBULATORY OESOPHAGEAL MANOMETRY

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Keywords: Oesophagus, peristalsis, SOFM, Kohonen,

Abstract

Gastrointestinal (GI) diseases, the third most common cause of deaths in the UK (59,685 in 2000) have increased by 25% in the last ten years. Gastro-oesophageal reflux disease (GORD) has a prevalence of 20-40% in the population. Ten to 15% of GORD patients have Barrett’s oesophagus, a change in the cell lining of the oesophagus linked to oesophageal cancer. With a 5 year survival of 9% and annually 7000 new cases (12 per 100,000) oesophageal cancer has increased by 50% in the last 20 years. Barrett’s oesophagus is associated with poor motility, reflux and hiatus hernia [2].

Oesophageal manometry is used to investigate oesophageal motility. Patterns of pressure changes are seen as peristaltic waves pass over transducers on a catheter within the oesophagus. The standard investigation has many problems, as symptoms rarely occur during the short investigation time period. Also, despite widespread use it is not clear what values and patterns are important. Ambulatory manometry, introduced in 1985 to address these issues, has proved unpopular due to the large amounts of data generated which has proved difficult to analyse. Manual analysis is very time consuming while current software analysis, using predefined rules to detect peaks and classify patterns, is not always trusted and has not advanced over the last 20 years.

Our approach has been to use Kohonen self organising feature maps to classify the patterns of data that occur over 24 hours. Following a simple process of identifying candidate periods (feature vectors) this technique was used to automatically find patterns or clusters within the raw data. The early results have shown that patterns of oesophageal manometry data can be identified. Different patterns can be analysed and variation in occurrence rates detected during specific symptomatic periods. The results suggest that this approach may enable detection and help quantify differences in 24 hour manometry data between healthy controls and patients with Barrett’s oesophagus.

1 Introduction

1.1 Background

The analyses of Gastrointestinal (GI) measurements have not been a priority within the Medical Engineering community. This is probably due to the relative difficulty of the invasive technique and the relatively small number of GI Investigation Units in the UK. However, oesophageal dysfunction is indicated in a wide range of serious upper GI disorders as shown in Table 1.

<table>
<thead>
<tr>
<th>Disorder</th>
<th>Brief description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gastro-oesophageal reflux disease</td>
<td>Symptoms of heartburn may be accompanied by erosions of the oesophagus (oesophagitis)</td>
</tr>
<tr>
<td>Non cardiac chest pain</td>
<td>Chest pain that may be similar to that associated with heart but has a possible GI source</td>
</tr>
<tr>
<td>Diffuse oesophageal spasm</td>
<td>Diagnosed from manometry where complex multi-peaked pressures are seen in the oesophagus</td>
</tr>
<tr>
<td>Ineffective motility</td>
<td>Diagnosed from manometry and radiology. Poor clearance and low peristaltic pressures</td>
</tr>
<tr>
<td>Achalasia</td>
<td>Diagnosed from radiology and manometry and seen as absence of peristalsis and failure of lower oesophageal sphincter to relax</td>
</tr>
<tr>
<td>Barrett’s oesophagus</td>
<td>Diagnosed from endoscopy and histology. Pre cancerous change in cell type of distal oesophageal mucosa as a result of chronic exposure to acid reflux</td>
</tr>
</tbody>
</table>

Table 1: Disorders relating to the oesophagus and upper GI tract.

Typically a patient with symptoms indicating an upper GI disorder undergoes a series of studies including, endoscopy to visually examine the lining of the oesophagus and stomach, and a barium swallow to investigate function and structure and look for strictures or carcinomas. Ambulatory pH recording is used to investigate acid reflux, where a pH transducer is placed in the oesophagus on a transnasally intubated catheter. Oesophageal manometry, also using a transnasal catheter (see Figure 1 and 2), is used to measure pressures in the oesophagus to investigate peristalsis. These investigations are often combined together [6].
These examinations form the basis of diagnosing an upper GI disorder and the basis of therapeutic options including medical therapy and surgical remodelling of the gastro-oesophageal junction, a major undertaking.

Figure 1: Figure showing the typical placement of a manometry catheter in the oesophagus during ambulatory oesophageal manometry

The focus of our recent work has been on developing new methods for investigating ambulatory manometry recordings. Despite considerable amounts of clinical research regarding the pressures measured in the oesophagus little has changed in the basic techniques of analysis. Typically, there are two approaches to a standard analysis of oesophageal manometry. The first approach is a qualitative analysis involving visually inspecting the recording and comparing it with historical data and looking for unusual or distinct patterns that have been recognised. The second approach involves carrying out a quantitative analysis. A simple peak detection algorithm is usually implemented. Following which parameters such as peak height, width and peristaltic wave velocity are calculated [3]. The parameters of the algorithm such as threshold level and minimum peak height are set by the clinician. The values obtained are then compared with control values. However, the range of normal values for peristaltic peaks varies widely.

Sequences of peaks are sometimes classified by comparing the peaks found in a time window with a library of patterns (See Figure 2). A range of similar approaches have been used to classify the patterns observed [1] and most equipment manufactured employ a rules based peak detection and pattern matching system. It is important to note that the parameters used in these algorithms are often capable of being modified by the user and currently no standard exists.

Patterns and waves that do not meet the criteria are often very difficult to consider. The importance of the more complex signals and non peristaltic oesophageal signals and the effect of other contributing pressure components from movement, respiration and blood pressure are poorly understood (Note: The aorta and oesophagus are in close physical contact).

1.2 Research aims

Early work using supervised neural networks to identify peaks instead of the rules based algorithm [7,8] has been reported. However, no attempt was made to classify the peaks and patterns using artificial intelligence methods. Following previous success at using the Kohonen self organizing feature map (SOFM) to classify the results from ambulatory pH studies [4] the aim of this work was to determine if this technique could be used to cluster ambulatory manometry data from two well defined cohorts, one of patients with Barrett’s oesophagus and the other a group of healthy controls. The main goals were to minimise the parameters used to select candidate data and to determine if this technique could be used to compare peaks and patterns observed in the clinical setting and also to determine any difference in the classes identified in the two groups.

2 Methods

2.1 Ambulatory manometry

The study was designed to look at the difference between patients with confirmed Barrett’s Oesophagus and healthy controls with no history of gastro-intestinal disease. Ethical approval was obtained before studies commenced. Following transnasal intubation of a three pressure solid state catheter the subjects underwent ambulatory 24 hour manometry

2.2 Selection of candidate vectors for classification

For the two groups, candidate events were selected for classification by passing a moving window over the data. The data was collected at 10 samples/S and a window width was select to be 15 seconds (i.e. a 150 sample feature vector).
Typical swallows last 5 seconds and a 15 second window captures the longest events that have been recognised. A candidate event was considered to exist if the highest value greater than a minimum threshold was seen in the centre of the window. In this way only two predefined parameters were used, the window width and a single threshold level. This threshold level was set at a 10mmHg following an initial series of experiments which showed that decreasing the threshold below this value resulted in a rapid increase in events that on inspection were low level noise (Figure 3). This pre-processing was carried out in MATLAB (Mathworks,US).

2.3 Analysis using the Kohonen SOFM

The events were analysed for the pressures recorded at the 2nd transducer, midway in the smooth muscle of the oesophagus. Measurements of pressure above this point may be more complex as a result of the initialisation of the swallow and impact of striated muscle [5]. Measurements below this point towards the distal oesophagus may have additional complexity as a result of the sphincter between the oesophagus and stomach. Once the candidate windows had been selected the two groups were analysed separately using a Kohonen SOFM. This was carried out using a dedicated neural network development system (Neuscience Ltd, Southampton, UK). The programme implemented the SOFM analysis following network design through a simple drag and drop interface. In practice the Kohonen was initially run with a high number of available classifications and then this number was reduced following inspection of the clusters. The results described are for a network with 25 available classifications.

3 Results

3.1 Classification of events and peaks

The overall approach taken showed that this technique appears to successfully cluster the different types of events seen during ambulatory manometry. Examples of peaks seen in these clusters are shown in Figure 4. The clusters of peaks showed quite different properties between the healthy controls and patients with Barrett’s oesophagus.

![Figure 3](image_url) Effect of threshold detection on the number of candidate events detected in 24 hours.

![Figure 4: Examples of peak clusters found.](image_url)

![Figure 5: Examples of classes detected (class average +/-SD) from healthy controls.](image_url)
3.2 Outliers

One of the advantages and properties of using a Kohonen network to classify data is that it has the ability to identify outliers. Figure 7 shows an example of an outlier class within the healthy control group. Investigation showed it to be a number of artefacts related to the disruption of the connector to the recorder.

3.3 Stationarity and changes in the numbers and nature of peaks in time.

Little is known about how the manometry signals change in time over the day although it is generally assumed to be a stationary system. Having classified the classes of events it was then possible to investigate how the events are distributed over time. Clinically, the goal is to determine if any of the specific events are associated with symptoms. This is particularly challenging due to the low frequency of symptoms and the wide range of events seen. Figure 8 shows how different classes are occurring at different times of the day. These results show how the swallowing system may not be stationary with different classes of peaks occurring at different rates through the day.

3.4 Differences between subjects

Our previous work has highlighted the nonlinear nature of oesophageal manometry recordings and the wide range of signals seen within a single subject and between subjects [5]. To an extent this can be seen by examining the distribution of events from different subjects within example classes from the healthy group. Figure 9a shows an example of a class that has a wide range of subject members, while figure 9b shows a class that has only a few members.
3.5 Detecting patterns of peaks

To date the approach taken has been to focus on the events occurring at a single site, midway in the oesophagus. Clinically, the analysis of oesophageal motility focuses not only on a single site but also on the pattern of events occurring over several sites i.e. to look for evidence of successful propulsive peristalsis.

Our recent work has involved extending the technique of clustering a single time series using the Kohonen SOFM as shown previously by creating a feature vector that includes the data from all the transducers (i.e. a 450 sample feature vector) and then clustering the identified patterns. The candidate selection algorithm was made so that at each time point the event detection criteria were checked for each transducer and in the case of an event occurring at any level the full window would be taken. Examples of these patterns clustered from a single subject are shown in Figure 10.

4 Discussion

4.1 Early results

The results of this approach appear very promising. For the first time we are beginning to see a mechanism to group and classify events occurring within the oesophagus without recourse to a set of arbitrary predefined parameters or overly relying on a subjective interpretation.

In answer to the questions and aims of the research: Firstly, the simple candidate selection technique and Kohonen SOFM clustering does appear to be effective at identifying and separating the data into classes that can be used by clinicians to further examine and investigate the data.

Secondly, the initial work does appear to show quite different classes of peaks and patterns between the two cohorts investigated i.e. healthy controls and patients with Barrett’s oesophagus. Patients with Barrett’s oesophagus have less well defined peaks with lower values i.e. reduced motility. It is unclear if the reduced motility is the reason for the Barrett’s oesophagus i.e. a reduction in acid clearance or a result of the damage to the mucosa. But these results may suggest that poor motility may be a factor in Barrett’s oesophagus. The next stage in this work involves using the SOFM classifier trained with the control data and re-querying this with the Barrett’s data and looking at the relative frequency of occurrence with in the classes identified and vice versa.

4.2 The requirement for an integrated data mining tool

The approach taken has utilized a number of software tools including the original instrumentation software used to record and capture the data, MATLAB and MS Excel (Microsoft,
US) for pre-processing and windowing the data, and a dedicated neural network based program. In practice an integrated suite of software is required for the clinician to take them through the process of data mining and comparing the results and classes between different patient groups and subjects.

So far, a key limitation of ambulatory manometry has been the time taken to review and analyse the recording. As part of this work we carried out a survey of GI Practitioners regarding the use and analysis of ambulatory manometry. The results showed that 76% thought that the main problem with ambulatory oesophageal manometry was in the analysis. 22% of clinicians let the computer do all the work for the analysis, but for the majority of clinicians, it takes between 1 to 4 hours as they have to check the computer’s assessment. Only 5% of clinicians feel ambulatory oesophageal manometry has progressed as a tool (in terms of understanding and analytical technique) during their time as a GI Practitioner. These results highlight there is further to go regarding the analysis of ambulatory manometry recordings.

As in other areas of medical signal analyses both supervised and unsupervised techniques may be useful in the recognition and identification of oesophageal disease signatures. However, it is important to recognise that the analysis of oesophageal manometry is not yet at the point where we can define the importance of the different types of signals or even the role or effect of non oesophageal sources of pressure such as respiration or blood pressures. All of these may have an influence on oesophageal function and motility.

Many of the modern techniques for clustering and analysis used on medical signals such as ECG, EEG and EMG have yet to be tested and implemented on GI data. There is therefore a great opportunity for researchers in the biomedical engineering field to use these techniques in the demanding, and less well studied area, of GI physiology. In addition, these techniques may be used to exclude signals that are not deemed of interest i.e. noise rejection. This alone could significantly improve the approach to analysis. For example when using a supervised network on a single subject our most recent work has shown that a network can be trained to successfully differentiate between ‘signals of interest’ and noise with a success rate of 97%, in a similar manner to previous studies [7,8].

5 Conclusions

Although the work presented is in its early stages, the use of Kohonen SOFM’s has enabled ambulatory oesophageal recordings to be analysed without recourse to arbitrary parameters. The features of the recordings such as the classes and patterns of peaks could be identified and compared between groups. This technique has enabled us to see differences between ambulatory manometry of patient’s with Barrett’s oesophagus and healthy controls. This work has also shown how patterns of noise and changes in the swallowing systems stationarity could be detected. However, further work is required to produce an integrated system to enable this type of analysis to be routinely carried out in the clinical setting. In addition, clinicians have identified the need for much more research in this field.

It is hoped this work will encourage researchers into this challenging field. For more information visit the Association of GI Physiologists (www.giphysiology.org) and the British Society of Gastroenterology (www.bsg.org.uk) web sites.

Acknowledgements

The work on developing the analysis was funded by the Medical Engineering Department of the Central Manchester and Manchester Children’s University Hospitals NHS Trust.

References


