ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΑΤΡΩΝ
ΤΜΗΜΑ ΙΑΤΡΙΚΗΣ    ΤΜΗΜΑ ΦΥΣΙΚΗΣ
ΔΙΑΤΜΗΜΑΤΙΚΟ ΠΡΟΓΡΑΜΜΑ ΜΕΤΑΠΤΥΧΙΑΚΩΝ
ΣΠΟΥΔΩΝ
ΣΤΗΝ
ΙΑΤΡΙΚΗ ΦΥΣΙΚΗ

ΜΕΤΑΠΤΥΧΙΑΚΗ ΕΡΓΑΣΙΑ

Μέθοδοι Επεξεργασίας σήματος Καρδιοτοκογραφίας κατά την διάρκεια του τοκετού

ΣΥΚΑΣ ΓΡΗΓΟΡΗΣ

ΠΑΤΡΑ 2014
METHODOLOGY DEVELOPMENT ALGORITHMS FOR PROCESSING AND ANALYSIS OF CARDIOTOCOGRAMS IN LABOR

SYKAS GRIGORIOS

PATRA 2014
SUPERVISOR
Professor George Nikiforidis

EXAMINING COMMITTEE
Professor George Nikiforidis
Assistant Professor George C. Kagadis
Assistant Professor Dimitrios Karnabatidis
ACKNOWLEDGEMENTS

I am grateful to Professor G. Nikiforidis for his faith and confidence towards me and for his contribution in the fulfillment of this thesis.

I am also grateful to Professor G. Kagadis for his faith and confidence towards me and for his contribution in the fulfillment of this thesis.

I would like to thank Dr. S. Tsantis for helping me to acquire knowledge and for his important guidance in wavelet, FCM theory and algorithms. I would also like to thank him for his valuable guidelines in writing scientific articles.

I wish to express my gratitude to my father Dimitris Sykas for working hard as long as he lived to provide me education. I also express my gratitude to my mother Evaggelia Syka and my sister Katerina Syka for all the help and support on the road from the kindergarten to the University.

Finally I also thank my loving wife Syni Kontopoulou and my son Dimitris Sykas for their constant support and encouragement during the years of that work.

Sykas Gregory
Abstract

**Purpose:** To develop and validate a computerised algorithm for the interpretation of the characteristics of the fetal heart rate (FHR) in labour.

**Materials and methods:** A computerised algorithm based on wavelet transform and Fuzzy C-means algorithm was developed to assess baseline, variability, the presence of accelerations and types of decelerations. Twenty four segments of intrapartum cardiotocographs (CTG) were interpreted using the algorithm and evaluated by seven expert observers. The results compared to assess inter observer variation and agreement between the computer and experts.

**Results:** Inter observer agreement for FHR baseline and the presence and type of decelerations was good (Interclass correlation coefficient (ICC), 0.93, 0.93 and 0.79 respectively).

**Conclusions:** The validation of a computerised algorithm is limited by inter observer variation. The prediction of baseline and decelerations is as good as clinical observers but is more reproducible.
Contents

CHAPTER 1

CARDIOTOCOGRAPHY PHYSICS & INSTRUMENTATION ........................................................................ 10

1. Introduction ............................................................................................................................ 10

2. Background Information ...................................................................................................... 12
   2.1 Baseline ............................................................................................................................. 14
   2.2 Baseline FHR Variability ............................................................................................... 14
   2.3 Accelerations .................................................................................................................... 17
   2.4 Decelerations ................................................................................................................... 17

3. Interpretation of the CTG .................................................................................................... 19

CHAPTER 2

CLUSTERING ALGORITHMS ...................................................................................................... 20

1. Introduction ............................................................................................................................ 20

2. Basic Clustering Algorithms ............................................................................................... 21

3. Fuzzy C-Means Clustering (Fcm) Algorithm ...................................................................... 23

CHAPTER 3

THE WAVELET TRANSFORM ................................................................................................... 26

1. Wavelet Theory ..................................................................................................................... 26

CHAPTER 4

WAVELET BASED ANALYSIS OF CARDIOTOCOGRAMS IN LABOR ........................................ 34

A. Previous Work ...................................................................................................................... 34

B. Discussion-criticism of previous works ............................................................................ 50

C. Proposed Algorithm ............................................................................................................ 52

D. Quantitative Results ............................................................................................................ 61

REFERENCES .......................................................................................................................... 63
CHAPTER 1

CARDIOTOCOGRAPHY PHYSICS & INSTRUMENTATION

1. Introduction

Cardiotocography (CTG) is the most commonly used biophysical method for assessment of a fetal state. It consists in recording and analysis of fetal heart rate (FHR) signal, uterine contraction activity and fetal movements. Proper heart activity is an indicator of adequate fetal blood oxygenation and shows that the central nervous system is intact and provides a good modulating control. When a nonreassuring foetal heart pattern is determined, surgical and/or medical intervention may be initiated to reduce the risk of foetal death and short- and long-term morbidity, including neurologic disability.

(CTG) is an alternative to intense intermittent auscultation with a head stethoscope (foetoscope), or a hand held Doppler ultrasound monitor, the traditional method of intrapartum (during labour) foetal monitoring performed by the obstetrical staff. (Minnesota Health Technology Advisory Committee, 1996)

Electronic foetal monitors (EFM) were developed in an attempt to better detect foetal distress and consequently improve delivery results. EFM continuously record the foetal heart rate (FHR) and uterine activity (UA) patterns during labour and produce tracings displayed on a paper strip. The FHR is monitored externally or internally using devices that are either held in place on the mother's abdomen by an elastic band or belt or by an electrode attached to the foetal scalp or breech. Maternal contractions can be monitored by an external device or by a catheter inserted into the uterine cavity.

Electronic foetal monitors became available for marketing in 1968. By the mid 1970s, EFM had become controversial because it was suspected of being associated with
unnecessary caesarean deliveries (Ingemarsson, 1991). It is believed that confusion about interpretation and clinical use of this technology were factors in the increased number of caesarean sections being performed. The CTG trace is very difficult to interpret and there is no agreed reference point to which foetal heart rate patterns and uterine contraction patterns can be assessed. The CTG trace has been, so far, at some extend, interpreted on an empirical basis and thus it is not only subjective but also depends upon the experience of the obstetricians. It has been proven that there is a significant interobserver variability in the assessment of the cardiotocograms (Nielsen, 1987; Donker, 1993; Taylor, 2000). It was only when the foetal heart beat could be rather easily detected by means of ultrasound (the Doppler-shift) or through the application of direct electrocardiography, that cardiotocography became popular as the method to monitor the condition of the foetus. Currently the majority of obstetric decisions to assist delivery of the baby by artificial means (Caesarean section, forceps or vacuum extraction) for reasons of suspected foetal distress, relies on information gathered through the application of cardiotocography (CTG).

The CTG consists of two patterns, The foetal heart rate (FHR) and the uterine contractions (UC). Both are shown in figure 1.1

![Figure 1.1](image.png)

**Figure 1.1** A CTG trace. The y-scale is in beats per minute (bpm) and the x-scale is in minutes.
It is the obstetrician’s reassurance that the foetal heart rate (FHR) pattern is normal and the nearly 100% certainty that the foetus is in a good condition, which has made cardiotocography so attractive and has induced its widespread use. (Van Geijn, 1998).

Per partum fetal heart rate (FHR) monitoring aims at reducing neonatal morbidity and mortality due to asphyxia. Intrapartum foetal asphyxia is responsible for 30% of cerebral palsy in term neonates. Commonly, in making their decisions, obstetricians analyze FHR visually and follow the International Federation of Gynecology and Obstetrics (FIGO)-guidelines or the American College of Obstetricians and Gynecologists (ACOG). Classification and guidelines approach has shown to exhibit high sensitivity (high True Positive rate); however, at the price of very low specificity (high False Positive rate) to detect fetal asphyxia and subsequent cerebral palsy. This results in a significant number of unnecessary operative deliveries (instrumental delivery, caesarean) performed for fetuses showing at birth, hence a posteriori, no sign of asphyxia (False Positives). Compared to spontaneous vaginal delivery, operative deliveries are associated with higher short and long-term morbidity risk, both for the newborn and for the mother. For that reason, providing obstetricians with a robust and efficient statistical index aiming at assisting them in detecting per partum asphyxia efficiently constitutes an important goal and challenge in daily clinical practice (P. Abry 2011).

2. Background Information

FHR is mainly regulated by the autonomic nervous system whose activity highly depends on blood oxygenation content and pressure. This makes quantitative and systematic analysis of per partum FHR meaningful for predicting asphyxia. The automated and statistical analysis of FHR during labor, however, appears challenging, especially since FHR during labor is highly nonstationary and continuously evolving until delivery.

The analysis of FHR is an essential element of diagnostic process for fetal evaluation during pregnancy and labour. In the classical approach, a graphical representation of FHR signal is interpreted by clinician, whose task is to identify and classify the signal patterns. The basal level of FHR signal (called baseline) and its variability in the
aspect of transient increase (acceleration pattern) or decrease (deceleration pattern) is the primary subject of clinical assessment. Accelerations are the result of fetal movements and identify the fetal wellbeing, while decelerations are the symptoms of fetal distress usually indicating the risk of fetal hypoxia. Visual analysis of FHR recording does not ensure a correct assessment of the fetal state and the relevance of the interpretation depends on clinician’s experience.

It is necessary to have an interpretation of the CTG signal based on its characteristics which are:

- Baseline of FHR signal
- Baseline FHR variability
- Accelerations
- Decelerations
- Changes or trends in FHR patterns over time
- Frequency and intensity of uterine contractions

These features will be discussed below in more detail.

*Figure 1.2. Properties of the CTG pattern (Maeda, 1990)*
2.1 Baseline

Baseline foetal heart rate is the mean level of the FHR when this is stable, acceleration and decelerations being absent. It is determined over a time of period of 5 to 10 min and expressed in beats per minute (bpm) (FIGO, 1987)

- **Foetal bradycardia** is a baseline FHR less than 110 beats per minute lasting 10 minutes or longer and is the initial response of the healthy foetus to asphyxia. A baseline of 100-119 bpm in the absence of other non-reassuring patterns is not usually a sign of compromise (ACOG technical bulletin, 1995)
- **Moderate bradycardias** (80 to 100 BPM for more than 3 minutes) may be associated with foetal head compression
- **Severe bradycardias** (less than 80 BPM for more than 3 minutes) may be associated with foetal acidosis (Minnesota Health Technology Advisory Committee, 1996).
- **Foetal tachycardia** is defined as a baseline FHR greater than 160 BPM lasting for 10 minutes or longer and represents an early compensatory response to asphyxia or may be a response to certain maternal medications.(maternal fever, foetal hypoxia, foetal anemia, amnionitis, foetal tachyarrhythmia)
- **Mild tachycardia** is defined as 161 to 180 BPM.
- **Severe tachycardia** is more than 180 BPM.

Foetal tachycardia may be a sign of increased foetal stress when it persists, but it is usually not associated with severe foetal distress unless there is increased variability or other abnormalities (Minnesota Health Technology Advisory Committee, 1996).

2.2 Baseline FHR Variability

The foetal heart rate varies from one beat to the next, because two branches of the autonomous nervous system control changes in the FHR. The sympathetic division is constantly trying to increase the FHR, while the parasympathetic division is trying to counteract this by slowing the FHR. Two components of FHR variability have been described: short term and long term.

- **Short term variability** is defined as beat-to-beat variation and it is normally 5 to 10 BPM. The beat-to-beat variation is reliable only in case of internal
recording of the FHR. When external recording is used then the record is only approximate the difference in heart rate drawn on the CTG.

- **Long term variability** is defined as the fluctuations of the FHR observed along the baseline, excluding accelerations and decelerations. In the FHR tracings, short term variability is superimposed on long term variability in the form of minimal deflexions. However, these cannot be reliably interpreted by the naked eye using the standard equipment. Therefore, in clinical practice, variability means long term variability (FIGO, 1987). It is determined over a time period of 5 or 10 minutes and expressed in BPM. It is assessed during a reactive period in segments of one minute showing the greatest band width.

Long term variability is characterised by the frequency and the amplitude of the oscillations. Although the frequency may be important, it is difficult to assess correctly. Therefore variability is usually only quantified by description of the amplitude of the oscillations around the baseline heart rate (FIGO, 1987).

The grades of baseline variability are based on amplitude range. If variability is absent the amplitude range is undetectable.

- **Silent or minimal** → less than 5 bpm
- **Reduced** → between 6 and 10 bpm
- **Normal** → between 10 and 25 bpm
- **Increased or salutatory** → above 25 bpm

*(National Institute of Child Health and Human Development Research Planning Workshop 1997)*
The saltatory pattern is characterised by leaping or dancing, proceeding by abrupt movements or changing by sudden deviation. This pattern is induced by foetal hypoxemia (Petrie, 1978). It is reported that reduced variation over 60 minutes is associated with chronic hypoxemia (Dawes, 1991) and increased variability is a reflection of excessive vagal activity (Goodlin, 1974). Excluded from the definition of the variability is an FHR pattern classified as sinusoidal pattern and is shown in next figure (1.4). This is a sine wave-like pattern of regular frequency and amplitude. It is going 5-15 BPM above and then below the baseline at a rate of 3-5 times per minute for 10 minutes or longer (ACOG, 1995). This pattern is associated with severe anaemia or hypoxic foetuses (Modanlou, 1982) and cannot be distinguished by intermittent auscultation.
2.3 Accelerations

The definition of an acceleration depends on the gestational age (GS) of the foetus. If the GS is less than 32 weeks, acceleration occurs when the FHR signal is 10 bpm greater from the baseline for 10 seconds or more. If the GS is greater than 32 weeks, acceleration occurs when the FHR signal is 15 bpm greater from the baseline for 15 seconds or more (National Institute of Child Health and Human Development Research Planning Workshop, 1997). The presence of at least two accelerations during a 10-minute period is a sign of good health for the foetus (FIGO, 1987). The accelerations provide evidence of foetal well-being and are generally considered reassuring. The presence of spontaneous or induced accelerations rules out significant metabolic acidosis. However, if sustained and associated with a lack of variability, this pattern may indicate early foetal distress.

![Fetal Heart Rate and Uterine Contractions](image)

Figure 1.5. An example of accelerations (Cabanis, 1993)

2.4 Decelerations

The deceleration is defined as a transient episode of slowing of foetal heart rate below the baseline of more than 15 BPM and lasting 10 seconds or more (FIGO, 1987). Each deceleration has a corresponding uterine contraction (National Institute of Child Health and Human Development Research Planning Workshop, 1997).

The reason of any deceleration is uterine hyperactivity, cord prolapse and cord compression, abruption, artefact (maternal heart rate), maternal seizure (Boehm & Crowdon, 1974). Foetuses with shorter contraction to deceleration intervals (latency period) exhibit a more pronounced degree of hypoxia than those with a longer latency period (Gaziano & Freeman, 1977). The decelerations are classified as: early, late, variable and prolonged. This classification is based upon the temporal...
relationship between the minimum of the deceleration and the maximum of the associated uterine contraction.

- **Early decelerations.** The lowest point of the FHR signal occurs when we have the peak of a uterine contraction. The recovery of an early deceleration is fast. They occur usually due to head compression. Early decelerations usually occur within the normal foetal heart rate, usually do not fall more than 20 to 30 bpm or below 100 bpm. They often last less than 90 seconds and are related to the strength of the uterine contraction. The FHR returns to normal when the contraction ends (Minnesota Health Technology Advisory Committee, 1996).

- **Late decelerations.** Late decelerations are transitory decreases in FHR that occur after a contraction begins. FHR does not return to baseline levels until well after the uterine contraction has ended (15 to 30 seconds after the uterine contraction peak). It is well established that certain FHR properties, such as late decelerations, are likely to be associated with intrapartum and neonatal depression (Gaziano & Freeman, 1977). These patterns may be associated with persistent hypoxia or foetal acidosis or may be caused by a transient insufficiency of uterine blood flow (Minnesota Health Technology Advisory Committee, 1996). Regardless of the depth of the deceleration, all late decelerations are considered potentially ominous.

- **Variable decelerations** Variable decelerations are a combination of the previous two types and vary greatly in shape from contraction to contraction. They may bear no consistent relationship to uterine contractions. Variable decelerations are not associated with significant changes in the foetal acid-base status unless the FHR changes are frequent, profound and prolonged (Young, 1980). When this pattern decreases to less than 70 BPM, persists at that level for at least 60 seconds, and is repetitive then it becomes concerning. Those with persistently slow return to baseline are also considered non-reassuring, as these reflect hypoxia beyond the relaxation phase of the contraction.
- **Prolonged decelerations.** A prolonged deceleration, often incorrectly referred to as bradycardia, is an isolated, abrupt decrease in the FHR to levels below the baseline that lasts at least 60-90 seconds and up to 10 minutes. These changes are always of concern and may be caused by virtually any mechanism that can lead to foetal hypoxia. The degree to which such decelerations are non-reassuring depends on their depth and duration, loss of variability, response of the foetus during the recovery period, and, most importantly, the frequency and progression of recurrence (ACOG, 1995)

3. **Interpretation of the CTG**

The patterns of the intrapartum foetal cardiotocograms are classified as normal, suspicious or pathological according to FIGO criteria:

Normal pattern is characterised by a baseline heart rate between 110 and 150 BPM and an amplitude of variability between 5 and 25 BPM. We also have total absence of decelerations except of sporadic, mild ones of very short duration and finally the presence of two or more accelerations during a 10-minute segment.

Suspicious pattern is characterized by any of the following signs are present:

A baseline heart rate between 170 and 150 BPM or between 110 and 100 BPM. An amplitude of variability between 5 and 10 BPM for more than 40 minutes. An increased variability above 25 BPM and finally the existence of variable decelerations.

Pathological pattern is characterized by any of the following signs are present: A baseline foetal heart rate below 100 or above 170 BPM. Persistence of heart rate variability of less than 5 BPM for more than 40 minutes. Severe variable decelerations or severe repetitive early decelerations. We have prolonged and late decelerations. The most ominous trace is a steady baseline without baseline variability and with small decelerations after each contraction. The Sinusoidal pattern has frequency less than 6 cycles/min, amplitude at least 10 bpm and its duration should be 20 minute or longer.
CHAPTER 2

CLUSTERING ALGORITHMS

1. Introduction

Clustering is an unsupervised learning task that aims at decomposing a given set of objects into subgroups or clusters based on similarity. The goal is to divide the data-set in such a way that objects (or example cases) belonging to the same cluster are as similar as possible, whereas objects belonging to different clusters are as dissimilar as possible. The motivation for finding and building classes in this way can be manifold [17]. Cluster analysis is primarily a tool for discovering previously hidden structure in a set of unordered objects. In this case one assumes that a ‘true’ or natural grouping exists in the data. However, the assignment of objects to the classes and the description of these classes are unknown. By arranging similar objects into clusters one tries to reconstruct the unknown structure in the hope that every cluster found represents an actual type or category of objects. Clustering methods can also be used for data reduction purposes. Then it is merely aiming at a simplified representation of the set of objects which allows for dealing with a manageable number of homogeneous groups instead of with a vast number of single objects. Only some mathematical criteria can decide on the composition of clusters when classifying data-sets automatically. Therefore clustering methods are endowed with distance functions that measure the dissimilarity of presented example cases, which is equivalent to measuring their similarity. As a result one yields a partition of the data-set into clusters regarding the chosen dissimilarity relation.

All clustering methods that we consider in this chapter are partitioning algorithms. Given a positive integer K, they aim at finding the best partition of the data into K groups based on the given dissimilarity measure and they regard the space of possible partitions into K subsets only.
A common concept of all described clustering approaches is that they are prototype-based, i.e., the clusters are represented by cluster prototypes $M_j, j=1, \ldots, K$. Prototypes are used to capture the structure (distribution) of the data in each cluster. With this representation of the clusters we formally denote the set of prototypes $M= \{M_1, \ldots, M_K\}$. Each prototype $M_j$ is an $n$-tuple of parameters that consists of a cluster center $\mu_i$ (location parameter) and maybe some additional parameters about the size and the shape of the cluster. The cluster center $\mu_i$ is an instantiation of the attributes used to describe the domain, just as the data points in the data-set to divide. The size and shape parameters of a prototype determine the extension of the cluster in different directions of the underlying domain. The prototypes are constructed by the clustering algorithms and serve as prototypical representations of the data points in each cluster.

2. Basic Clustering Algorithms

Clustering algorithms are used extensively not only to organize and categorize data, but are also useful for data compression and model construction [18].

In this section, we present the fuzzy C-means, deriving it from the hard c-means clustering algorithm. The latter one is better known as k-means, but here we call it (hard) C-means to unify the notation and to emphasize that it served as a starting point for the fuzzy extensions. We further restrict ourselves to the simplest form of cluster prototypes at first. That is, each prototype only consists of the center vectors, $C_i=(c_i)$, such that the data points assigned to a cluster are represented by a prototypical point in the data space. We consider as a distance measure $d$ an inner product norm induced distance as for instance the Euclidean distance.

All algorithms described in this section are based on objective functions $Q$, which are mathematical criteria that quantify the goodness of cluster models that comprise prototypes and data partition. Objective functions serve as cost functions that have to be minimized to obtain optimal cluster solutions. Thus, for each of the following cluster models the respective objective function expresses desired properties of what should be regarded as “best” results of the cluster algorithm. Having defined such a criterion of optimality, the clustering task can be formulated as a function
optimization problem. That is, the algorithms determine the best decomposition of a data-set into a predefined number of clusters by minimizing their objective function. The steps of the algorithms follow from the optimization scheme that they apply to approach the optimum of Q. Thus, in our presentation of the hard and fuzzy c-means we discuss their respective objective functions first. Then we shed light on their specific minimization scheme.

The idea of defining an objective function and have its minimization drive the clustering process is quite universal. Aside from the basic algorithms many extensions and modifications have been proposed that aim at improvements of the clustering results with respect to particular problems (e.g., noise, outliers). Consequently, other objective functions have been tailored for these specific applications. However, regardless of the specific objective function that an algorithm is based on, the objective function is a goodness measure. Thus it can be used to compare several clustering models of a data-set that have been obtained by the same algorithm (holding the number of clusters, i.e., the value of μ).

In their basic forms the hard and fuzzy C-means algorithms look for a predefined number of K clusters in a given data-set, where each of the clusters is represented by its center vector. However, hard and fuzzy C-means differ in the way they assign data to clusters, i.e., what type of data partitions they form. In classical (hard) cluster analysis each datum is assigned to exactly one cluster. Consequently, the hard C-means yield exhaustive partitions of the example set into non-empty and pairwise disjoint subsets. Such hard (crisp) assignment of data to clusters can be inadequate in the presence of data points that are almost equally distant from two or more clusters. Such special data points can represent hybrid-type or mixture objects, which are (more or less) equally similar to two or more types. A crisp partition arbitrarily forces the full assignment of such data points to one of the clusters, although they should (almost) equally belong to all of them. For this purpose the fuzzy clustering approaches presented in Section 2.3 fulfill the requirement that data points have to be assigned to one (and only one) cluster. Data points can belong to more than one cluster and even with different degrees of membership to the different clusters. These gradual cluster assignments can reflect present cluster
structure in a more natural way, especially when clusters overlap. Then the memberships of data points at the overlapping boundaries can express the ambiguity of the cluster assignment.

The shift from hard to gradual assignment of data to clusters for the purpose of more expressive data partitions founded the field of fuzzy cluster analysis. We start our presentation with the hard C-means.

3. Fuzzy C-Means Clustering (Fcm) Algorithm

Fuzzy cluster analysis allows gradual memberships of data points to clusters measured as degrees in [0,1]. This gives the flexibility to express that data points can belong to more than one cluster. This method was developed by Bezdek in 1981. Furthermore, these membership degrees offer a much finer degree of detail of the data model. Aside from assigning a data point to clusters in shares, membership degrees can also express how ambiguously or definitely a data point should belong to a cluster. The concept of these membership degrees is substantiated by the definition and interpretation of fuzzy sets.

Let \( V = \{v_1, \ldots, v_n\} \) be the set of given examples and let \( c \) be the number of clusters \( 1 < c < n \). Then we call \( u_{ij} \) a probabilistic cluster partition of \( V \) if

\[
\sum_{j=1}^{n} u_{ij} > 0, \forall i = \{1, \ldots, C\} \tag{2.2}
\]

and

\[
\sum_{i=1}^{C} u_{ij} = 1, \forall j = \{1, \ldots, n\} \tag{2.3}
\]

The \( u_{ij} \in [0,1] \) are interpreted as the membership degree of datum \( v_j \) to cluster \( i \) relative to all other clusters. Constraint (2.2) guarantees that no cluster is empty. This corresponds to the requirement in classical cluster analysis that no cluster, represented as (classical) subset of \( V \), is empty. Condition (2.3) ensures that the sum of the membership degrees for each datum equals 1. This means that each datum receives the same weight in comparison to all other data and, therefore, that all data
are (equally) included into the cluster partition. As a consequence of both constraints no cluster can contain the full membership of all data points. Furthermore, condition (2.3) corresponds to a normalization of the memberships per datum. Thus the membership degrees for a given datum formally resemble the probabilities of its being a member of the corresponding cluster.

After defining probabilistic partitions we can turn to developing an objective function for the fuzzy clustering task. Certainly, the closer a data point lies to the center of a cluster, the higher its degree of membership should be to this cluster. Following this rationale, one can say that the distances between the cluster centers and the data points (strongly) assigned to it should be minimal. Hence the problem to divide a given data-set into c clusters can (again) be stated as the task to minimize the squared distances of the data points to their cluster centers, since, of course, we want to maximize the degrees of membership. The probabilistic fuzzy objective function Q is thus based on the least sum of squared distances.

More formally, a fuzzy cluster model of a given data-set V into c clusters is defined to be optimal when it minimizes the objective function:

\[
Q = \sum_{i=1}^{n} \sum_{j=1}^{C} \mu_{ij}^m \|v_j - \mu_i\|^2 \quad 1 \leq m < \infty
\]

under the constraints (2.2) and (2.3) that have to be satisfied for probabilistic membership degrees in Q. The condition (2.3) avoids the trivial solution of minimization problem, i.e., \(u_{ij} = 0 \ \forall \ i, j\). The normalization constraint (2.3) leads to a ‘distribution’ of the weight of each data point over the different clusters. Since all data points have the same fixed amount of membership to share between clusters, the normalization condition implements the known partitioning property of any probabilistic fuzzy clustering algorithm. The parameter \(m, m > 1\), is called the fuzzifier or weighting exponent. The actual value of \(m\) determines the ‘fuzziness’ of the classification. The generalization for exponents \(m > 1\) that lead to fuzzy memberships has been proposed in Bezdek, 1973 [25]. With higher values for \(m\) the
boundaries between clusters become softer, with lower values they get harder. Usually m=2 is chosen.

The membership degrees have to be chosen according to the following formula that is independent of the chosen distance measure:

$$u_{ij}^m = \frac{1}{\sum_{k=1}^{C} \left( \frac{||v_j - \mu_i||}{||v_j - \mu_k||} \right)^{\frac{2}{m-1}}}$$  \hspace{1cm} (2.5)

In this case there exists a cluster i with zero distance to a datum v_j, u_{ij}=1 and u_{kj}=0 for all other clusters k ≠ i. The above equation clearly shows the relative character of the probabilistic membership degree. It depends not only on the distance of the datum v_j to cluster i, but also on the distances between this data point and other clusters.

The cluster center estimated:

$$\mu_i = \frac{\sum_{i=1}^{n} u_{ij}^m v_i}{\sum_{i=1}^{n} u_{ij}^m}$$  \hspace{1cm} (2.6)

Where:

c - the number of cluster centers or data subsets

m - the weighting exponents

||v_j - \mu_i||^2 - the distance measure between object v_j and cluster center \( \mu_i \);

n - the total number of pixels in image;

u_{ij} - the fuzzy membership membership matrix

\( \mu_i \) - the cluster center for subset i in feature space;

U – the fuzzy c-partition

Q - objective function
CHAPTER 3

THE WAVELET TRANSFORM

1. Wavelet Theory

Wavelets are an extension of windowed Fourier analysis by Gabor [52], in which through a fixed window a large number of oscillations are used for detecting high frequencies, whereas a small number is used to detect low frequencies. However, in the first case the window is ‘blind’ to smooth events and in the second case the window probably will miss a brief change. Instead of a fixed window and a variable number of oscillations Morlet and Grossman [53] employed a ‘mother wavelet’ which is stretched or compressed to change the size of the window, thus providing a decomposition of the signal at different scales (frequency bands). The dilation of the function called ‘mother wavelet’ produces a family of functions. The wavelet transform of a signal is a sequence of signals obtained by the convolution of the signal with the wavelet family. The wavelets size variation due to dilation permits them to automatically adapt to the different components of the signal. A small window (high frequency band) detects rapid high-frequency components and a large window (low frequency band) traces slow low-frequency components. The wavelet transform is required to satisfy a so called admissibility condition so that it can form a complete and numerically stable representation. The wavelet transform gives a representation that has good localization in both frequency and space [54-56]. The localization in frequency implies a correspondence between a scale of the wavelet transform and a frequency band. The overall study across all available frequency bands is called multiresolution analysis [57-59]. The wavelet transform is divided in two main categories: the continuous wavelet transform (CWT) in which all values of the parameters are employed and the discrete wavelet transform (DWT) in which only a discrete set of parameters are considered.
2. Continuous Wavelet Transform

The continuous wavelet transform is shift invariant thus suitable for feature extraction and image analysis methods [62]. The CWT decomposes a signal by means of dilated and translated wavelets. Let a wavelet $\psi(x) \in L^2(\mathbb{R})$ be a function of zero average:

$$\int_{\mathbb{R}} \psi(x) dx = 0$$  \hspace{1cm} (3.1)

It is normalized $\|\psi\| = 1$ and centered in the neighborhood of $x = 0$. The function $\psi(x)$ is used to create a wavelet family by dilating $\psi$ with $s$:

$$\psi_s(x) = \frac{1}{s} \psi \left( \frac{x}{s} \right)$$  \hspace{1cm} (3.2)

All the functions in the wavelet family have the same shape as the wavelet. The continuous wavelet transform of a signal $f \in L^2(\mathbb{R})$ is a family of functions $\left\{W_s f(x)\right\}_{s \in \mathbb{R}^+}$ and defined by:

$$W_s f(x) = \psi_s f(x), s \in \mathbb{R}^+$$  \hspace{1cm} (3.3)

If $\hat{\psi}(\omega)$ is the Fourier transform of $\psi(x)$, then:

$$\hat{W}_s f(\omega) = \hat{\psi}(s\omega) \hat{f}(\omega)$$  \hspace{1cm} (3.4)

In order for the transform to be invertible, the wavelet $\psi(x)$ must satisfy the admissibility condition [53]:

$$C_\psi = \int_{\mathbb{R}^+} \left| \hat{\psi}(\omega) \right|^2 \frac{d\omega}{\omega} < +\infty$$  \hspace{1cm} (3.5)

The function $f(x)$ can be reconstructed from its wavelet transform [53]:

$$W^{-1} : f(x) = \int_{\mathbb{R}^+} \hat{\psi}_s \hat{W}_s f(x) \frac{ds}{s}$$  \hspace{1cm} (3.6)

The admissibility condition also ensures that the wavelet transform is an isometry:
\[ \|f(x)\|^2 = \int_0^\infty \|W_s f(x)\|^2 \frac{ds}{s} \]  

Equation 4.7 implies that the continuous wavelet transform is a complete and numerical stable representation.

3. Redundant Dyadic Wavelet Transform (1-D)

In the translation-invariant dyadic wavelet transform the scale parameter \( s \) is discretized dyadically \( ([2^j])_{j \in \mathbb{Z}} \) to simplify the numerical calculations, while the spatial parameter is continuous. Let a wavelet \( \psi(x) \in L^2(\mathbb{R}) \) is a wavelet whose average is zero. The wavelet family by dilating \( \psi \) with \( s \) is:

\[ \psi_{2^j}(x) = \frac{1}{2^j} \psi(\frac{x}{2^j}) \]  

The dyadic wavelet transform of a function \( f(x) \in L^2(\mathbb{R}) \), at a given scale \( 2^j \) and at the position \( x \) obtained by the convolution of \( f(x) \) with the wavelet family

\[ W_{2^j} f(x) = f(\psi_{2^j}(x)) \]  

We refer to the dyadic wavelet transform as the sequence of functions:

\[ Wf = (W_{2^j} f(x))_{j \in \mathbb{Z}}, \]  

where \( W \) is the dyadic wavelet transform operator.

In order to study the completeness and stability of the DWT we denote the Fourier transform of \( W_{2^j} f(x) \) as:

\[ \hat{W}_{2^j} f(\omega) = \hat{f}(\omega) \hat{\psi}(2^j \omega) \]  

Given that there are two strictly positive constants \( A \) & \( B \) such that:

\[ \forall \omega \in \mathbb{R}, A \leq \sum_{j \in \mathbb{Z}} |\hat{\psi}(2^j \omega)|^2 \leq B, \]  

it is ensured that the whole frequency axis is covered by dilations of \( \hat{\psi}(\omega) \) by \( (2^j)_{j \in \mathbb{Z}} \) so that \( \hat{f}(\omega) \) and consequently \( f(x) \) can be recovered from its dyadic wavelet.
The reconstructing wavelet $\chi(x)$ is any function whose Fourier transform satisfies:

$$\sum_{j=-\infty}^{+\infty} \tilde{\psi}(2^j \omega) \tilde{\chi}(2^j \omega) = 1.$$ \hspace{1cm} (3.13)

If equation (4.12) is valid, an infinite number of functions $\tilde{\chi}(x)$ exist that satisfy equation (4.13). The inverse dyadic wavelet transform that recovers $f(x)$ is given by the summation:

$$f(x) = \sum_{j=-\infty}^{+\infty} W_{2^j} f_{2^j}(\chi).$$ \hspace{1cm} (3.14)

In practice, we can compute a Wavelet Transform only over finitely many scales. This is because the observed data is limited between a non-zero small (fine) scale and a finite large (coarse) scale. According to Mallat [57], one can normalize the observable finest scale to $1(2^0)$ and the coarsest scale to $2^J$ where $J$ is dependent on the sample size of the data. In order to model this scale limitation, a real function $\phi(x)$ is introduced, whose Fourier transform is an aggregation of $\tilde{\psi}(2^j \omega)$ and $\tilde{\chi}(2^j \omega)$ at scales $2^j$ larger than 1:

$$\left|\tilde{\phi}(\omega)\right|^2 = \sum_{j=1}^{+\infty} \tilde{\psi}(2^j \omega) \tilde{\chi}(2^j \omega)$$ \hspace{1cm} (3.15)

The reconstructive wavelet $\chi(\omega)$ is such a function that $\tilde{\psi}(\omega) \tilde{\chi}(\omega)$ is a positive, real and even function. The equation (4.13) implies that the integral of $\phi(x)$ is equal to 1 and hence that it is a smoothing function. Let $S_{2^j}$ be the smoothing operator defined by:

$$S_{2^j} f(x) = f \quad \phi_{2^j}(x), \phi_{2^j}(x) = \frac{1}{2^j} \phi\left(\frac{x}{2^j}\right)$$ \hspace{1cm} (3.16)

If the scale $2^j$ is larger, the more details of $f(x)$ are removed by $S_{2^j}$. For any scale $2^j>1$ equation (4.15) yields:
\[ |\hat{\phi}(\omega)|^2 - |\hat{\phi}(2^j \omega)|^2 = \sum_{j=1}^{J} \hat{\phi}(2^j \omega) \hat{\chi}(2^j \omega) \]  

3.17

From this equation it is derived that the higher frequencies of \(S_2 f(x)\), which have disappeared in \(S_2 f(x)\) can be recovered from the dyadic wavelet transform \(\{W_{2^j} f\}_{1 \leq j \leq J}\) between the scale \(2^j\) and \(2^l\).

In numerical applications, the input signal is measured at a finite resolution and thus the wavelet transform cannot be computed at any arbitrary scale. The original signal can be considered as a discrete sequence \(D = [d_n]_{n \in \mathbb{Z}}\) of finite energy. If two constants \(C_1 > 0\) and \(C_2 > 0\) exist, such that \(\hat{\phi}(\omega)\) satisfies:

\[ \forall \omega \in \mathbb{R}, C_1 \leq \sum_{n=-\infty}^{+\infty} |\hat{\phi}(\omega) + 2n\pi|^2 \leq C_2 \]  

3.18

From Equation 4.18 the periodic signal \(D\) can be considered as the sampling of a smoothed version of \(f(x) \in L^2(\mathbb{R})\) at the finest scale 1:

\[ \forall n \in \mathbb{Z}, S_1 f(n) = d_n \]  

3.19

The input signal can thus be rewritten as \(D = [S_1 f(n)]_{n \in \mathbb{Z}}\). Mallat had proposed the redundant discrete wavelet transform (RDWT), utilizing a particular class of wavelets, to compute a uniform sampling of the wavelet transform of \(f(x)\) at any scale larger than 1.

Let us denote \(S_2^d f = [S_2 f(n+w)]_{n \in \mathbb{Z}}\) and \(W_2^d f = [W_2 f(n+w)]_{n \in \mathbb{Z}}\) where \(w\) is a sampling shift that depends on \(\psi(x)\). For any coarse scale \(2^l\) the sequence of discrete signals:

\[ \{S_2^d f, W_2^d f\}_{1 \leq j \leq J} \]  

3.20

is called the discrete dyadic wavelet transform of \(D = [S_1 f(n)]_{n \in \mathbb{Z}}\). The coefficient signal \([W_2^d f]\) provide the details of the input signal at scales \(1 \leq j \leq J\) and the coarse signal \(S_2^d f\) provides the approximation of the input signal at the coarse scale \(2^l\). The filter bank algorithm for computing 1-D RDWT is presented in Figure 4.1. The
left size shows the decomposition into wavelet coefficients and the right the reconstruction from wavelet coefficients.

**Figure 3.1** One-dimensional – three level – redundant discrete dyadic wavelet transform.

The algorithm does not involve sub-sampling and is similar to the ‘algorithme â trous’ (algorithm with holes), which also does not involve sub-sampling. Filters $H(\omega)$, $G(\omega)$ and $K(\omega)$, are $2\pi$ periodic and satisfy the perfect reconstruction condition:

$$\left|H(\omega)\right|^2 + G(\omega)K(\omega) = 1$$  \hspace{1cm} \text{(3.21)}

At dyadic scale $j$, the discrete filters $H_j$, $G_j$, $K_j$, are obtained by inserting $2^{j-1}$ zeros between each of the coefficients of the corresponding filters at scale $2^1$. The scaling (smoothing) function $\phi(x)$ defined in equation (4.15) can be derived from $H(\omega)$ using the equation:

$$\hat{\phi}(\omega) = e^{-i\omega w} \prod_{\rho=1}^{\infty} H(2^{\rho-1} \omega)$$ \hspace{1cm} \text{(3.22)}

where the sampling shift parameter $w$ is adjusted so that $\phi(x)$ is symmetrical with respect to 0. Equation (4.22) implies that

$$\hat{\phi}(2\omega) = e^{-i\omega w} H(\omega) \hat{\phi}(\omega)$$ \hspace{1cm} \text{(3.23)}

A wavelet $\psi(x)$ is defined, whose Fourier transform $\hat{\psi}(\omega)$ is given from the equation:

$$\hat{\psi}(2\omega) = e^{-i\omega w} G(\omega) \hat{\phi}(\omega)$$ \hspace{1cm} \text{(3.24)}

The reconstruction wavelet $\chi(x)$ is derived from the equation:
$$\hat{\chi}(2\omega) = e^{i\omega w}K(\omega)\hat{\phi}(\omega) \tag{3.25}$$

A class of filters that satisfy equation (4.21) has been provided by Mallat. $H(\omega)$ was chosen to obtain a wavelet $\psi(x)$ which is anti-symmetrical, as regular as possible and has a compact support. The wavelet $\psi(x)$ is also equal to the first order derivative (gradient) of a smoothing function $\vartheta(x)$:

$$\psi(x) = \frac{d\vartheta(x)}{dx} \tag{3.26}$$

Filters $H(\omega)$, $G(\omega)$ and $K(\omega)$ are given by:

$$H(\omega) = e^{i\omega/2} (\cos(\omega/2))^{2n+1} \tag{3.27}$$

$$G(\omega) = 4e^{i\omega/2} \sin(\omega/2) \tag{3.28}$$

$$K(\omega) = \frac{1 - |H(\omega)|^2}{G(\omega)} \tag{3.29}$$

All filters have compact support and are either symmetrical or anti-symmetrical. From equations (4.22 & 4.24) the corresponding scaling and wavelet functions can be derived as:

$$\hat{\phi}(\omega) = \frac{\sin(\omega/2)}{\omega/2}^{2n+1} \tag{3.30}$$

$$\hat{\psi}(\omega) = i\omega \frac{\sin(\omega/4)}{\omega/4}^{2n+2} \tag{3.31}$$

The Fourier transform of the smoothing function $\vartheta(x)$ is therefore:

$$\hat{\vartheta}(\omega) = \frac{\sin(\omega/4)}{\omega/4}^{2n+2} \tag{3.32}$$

We have chosen $2n+1=3$. In order to have a wavelet anti-symmetrical with respect to 0 and $\varphi(x)$ symmetrical with respect to 0, the shifting constant $w$ is equal to $\frac{1}{2}$. From equations (4.31 & 4.32) it can be proven that $\psi(x)$ is a quadratic spline wavelet with
compact support, while $\vartheta(x)$ is a Gaussian-like cubic spline whose integral is equal to 1. These functions are depicted in Figure 4.2.

![Figure 3.2](image)

**Figure 3.2** (a) A cubic spline function and (b) a wavelet that is a quadratic spline of compact support.

Mallat had extended this class of filters and derived wavelet functions $\psi(x)$ that are equal to the second order derivative (Laplacian) of a smoothing function.

$$
\psi(x) = \frac{d\vartheta^2(x)}{dx^2}
$$

3.33
WAVELET BASED ANALYSIS OF CARDIOTOCOGRAMS IN LABOR

A. Previous Work

Many scientists all over the world offer a variety of methods in the interpretation of FHR recordings. It is generally believed that the FHR signal may convey much more information than what is observed by obstetricians. We will present the most common and successful trials in our opinion during the last decade. The full article list is shown in the end of our presentation for any future researcher. In 2004 E. Salamalekis and his team made computerised intrapartum diagnosis of fetal hypoxia based on fetal heart rate monitoring and fetal pulse oximetry recordings, utilising wavelet analysis and neural networks. Data were collected randomly from 61 women during labour. The women were carrying singleton pregnancies of more than 37 weeks of gestation. The presentation was cephalic, and they were monitored after spontaneous or artificial rupture of membranes when cervical dilatation was more than 3 cm. Women with antepartum metabolic or endocrine disorders were not included in the study. Twelve cases, in which umbilical artery pH was lower than 7.20 and Apgar score was over 7 at 5 minutes were grouped together in the risk group. The rest of the women formed the normal group. Wavelet multiresolution analysis for each 10-minute segment in order to address the problem of long term non-stationary behaviour of the fetal heart rate tracings and to estimate the power in different frequency ranges. The multiscale feature of the wavelet transform allows the decomposition of a signal into a number of scales, each scale representing a particular ‘coarseness’ of the signal under study. This essentially decomposes the signal into a set of signals of varying ‘coarseness’ ranging from low frequency components progressively to high frequency components. In order to categorise the different 10-minute fetal heart rate patterns and the associated 10-minute segments, we used the self-organising map neural network with the Kohonen learning rule. Such a network consists of two layers: an input layer and a two-
dimensional output, Kohonen layer. Self-organising maps, also called topology-preserving maps, assume a topologic structure among the cluster units. They learn to recognise groups of similar input vectors, in such a way that neurones physically near each other in the neurone layer respond to similar input vectors. After using k-means clustering algorithm, the two-dimensional output layer of the self-organising map neural network was divided into three distinct clusters.

The sensitivity of the system was 83.3% and the specificity 97.9% for the detection of risk group cases. Fetal pulse oximetry seems to be an important additional source of information. Computerised analysis of the fetal heart rate monitoring and pulse oximetry recordings is a promising technique in objective intrapartum diagnosis of fetal hypoxia. Further evaluation of this technique is mandatory to evaluate its efficacy and reliability in interpreting fetal heart rate recordings.

In 2005 J. T. Paper, T. King, S. Flanders, M. Fox, & S. J. Kilpatrick checked the association of fetal heart rate patterns and fetal academia. The validity of the relationship between various fetal heart rate (FHR) patterns and fetal acidemia was the aim of this study. There was an examine of the published literature for evidence of such a relationship. Hypotheses based on assumptions in common clinical use were examined. The literature was searched for relationships between certain aspects of FHR patterns (e.g., degree of FHR variability, depth of decelerations), and fetal acidemia, or fetal vigor (5-minute Apgar score >7). Using standardized FHR nomenclature patterns were defined based on baseline FHR variability, baseline rate, decelerations, and accelerations. The following relationships were observed: (1) Moderate FHR variability was strongly associated (98%) with an umbilical pH>7.15 or newborn vigor (5-minute Apgar score>7). (2) Undetectable or minimal FHR variability in the presence of late or variable decelerations was the most consistent predictor of newborn acidemia, though the association was only 23%. (3) There was a positive relationship between the degree of acidemia and the depth of decelerations or bradycardia. (4) Except for sudden profound bradycardia, newborn acidemia with decreasing FHR variability in combination with decelerations develops over a period of time approximating one hour. The validity of the relationship between certain FHR patterns and fetal acidemia is supported by observations from the literature.
addition four assumptions commonly used in clinical management are supported. These conclusions need to be confirmed by a prospective examination of a large number of consecutive, unselected FHR patterns, and their relationship to newborn acidemia. Pending the completion of such studies, these observations can be used to justify certain aspects of current clinical management, and may assist in standardizing the diversity of opinions regarding FHR pattern management.

Also in 2005 G. Georgoulas (3) and his team proposed a novel method to detect fetuses suspicious of developing acidemia, based on features extracted mathematically from the FHR signal. The core of the proposed method was the use of Discrete Wavelet Transform (DWT) for the extraction of a suitable set of scale dependant features and the use of a Support Vector Machine (SVM) classifier, for the categorization of FHR, based on the extracted features. Wavelets are very appealing tools that are used in many biomedical applications, and have been used with considerable success for the analysis of the inter-beat intervals of heart rate. The most appealing characteristic of wavelets is that they can decompose a signal into a number of scales, each scale representing a particular “coarseness” of the signal under study. SVMs are a recently developed learning machine method and they have proved highly successful in a number of classification studies. They are very useful for real-life and difficult classification problems due to their intrinsic ability to generalize well for unknown data even when the training set is quite small.

The procedure consists of artifact removal, data segmentation with time windows ranging from 1 minute to 15 minutes close to delivery. Data with extreme noise were excluded. At the feature extraction for each FHR signal and for the corresponding time segment discrete wavelet transform was carried out up to scale. For each scale we calculated the corresponding standard deviation of the distribution of wavelet coefficients. For the classification different learning SVM was constructed with quite different non-linear decision surfaces based on how the inner product kernel is generated. This team achieved classification performance of 90% with a very good balance between normal and fetuses at risk. In this work we have experimented with the use of SVMs and scale dependant features as an advanced automated methodology to discriminate between fetuses with “normal” umbilical artery Ph
values and those who have a decreased umbilical artery Ph and are suspicious of developing metabolic acidosis. In 2007 A. Warrick and his team proposed a method that focused on the deceleration event, a momentary decrease in the FHR that may last from 15s to 5 min. Detection of these events is complicated by their varying length, morphology, and degrees of background variability as well as the distracting presence of artifactual events. Signal decomposition into orthogonal components is a standard approach for generating compact representations of non-stationary signals. Singular-spectrum analysis (SSA) is one such method which has only recently been applied in a sequential manner suitable for on-line analysis. The SSA technique uses the Karhunen-Loeve transform (KLT) to determine the main structure of the underlying signal. By restricting the signal representation to the eigenvectors containing the majority of the signal energy, a compact signal approximation can be extracted. Change-point detection algorithms attempt to detect the location of changes in the characteristics of time-series data. This paper will briefly present the key concepts underlying KL decomposition. An efficient discrete cosine transform (DCT) implementation of the on-line SSA algorithm applied to the classification of deceleration candidate events from a database of FHR tracings.

The standard SSA algorithm has been used successfully in many contexts where changes are infrequent. The efficient DCT implementation of SSA is of general applicability to these problems, especially where the processing data volume is large and the input signal is sufficiently correlated. In FHR analysis, the assumption of infrequent changes does not always apply and the modifications improve the resolution of single events within a series of similar events. Also in 2007 G. Georgoulas again proposed grammatical revolution to construct new artificial features from the actual ones. Grammatical evolution is an evolutionary methodology that, as in the case of genetic programming can evolve complete programs. In our case, the evolved programs are mathematical expressions/functions of the originally extracted features. These constructed artificial features are then used to classify the FHR signal. The procedure consists of 5 stages. The artifact removal module firstly detects a stable FHR segment. Stable segment is defined as the segment where the difference between five adjacent
samples is less than 10 beats/min. The signals had to be transformed into regularly sampled ones through a pseudo-sampling procedure before incorporating them into the larger available FHR data set. A time duration of 20 min as the time length of the segments is selected to be analyzed. The 20 min segments were selected as close as possible to the end of the recordings (as close as possible to delivery) in order to avoid time bias.

Then in the feature extraction there is a gather of information from different domains, (a) the time domain, (b) the frequency domain and (c) a set of morphological features such as the number of accelerations and decelerations. After that 160 recordings were the sample throughout a procedure called SMOTE (Synthetic minority oversampling Technique) which works in the feature space rather than the data space. The aim is to produce more balanced feature sets. Finally in the grammatical evolution stage we have 2 phases the construction and the evaluation phase using neural networks. In this phase a classification of data with an MLP trained using a hybrid algorithm and in the validation phase there is a separation of the samples in 10 non overlapping sets. The classifier, which also uses a hybrid method for training, along with the constructed features was tested using a set of real data achieving an overall performance of 90% specificity in discriminating the normal from academic fetuses. The grammatical evolution based method constructs features that give “optimal” results for the problem at hand, without trying to maximize the variance or the information of the features like other methods (which does not necessarily lead to better classification results). The proposed method identifies linear and nonlinear correlations among the originally extracted features and creates a set of new ones, which, in turn, feeds a nonlinear classifier.

In 2008 another team (Van Laar, M.M. Porath, C.H.L. Peters & S.G. Oei) presented a review in order to determine the diagnostic value of spectral analysis of heart rate variability, performed on the human fetus, to detect fetal hypoxemia or acidosis. All published studies that described spectral analysis of heart rate variability of the human fetus and compared spectral energy in specific frequency bands with blood-gas values, obtained by funipuncture or from the umbilical cord immediately
postpartum, were included in the study. The outcome measures of interest were blood-gas values in the umbilical vessels (pH, PO$_2$, base excess or base deficit).

Spectral analysis determines the energy in specific frequency components of heart rate variability. The low frequency (LF) component reflecting baroreceptor reflex activity is sympathetically and parasympathetically mediated, and the high frequency (HF) component is associated with respiration and parasympathetic nerve activity. The ratio of the low frequency and high frequency powers (LF/HF) provides a marker of the sympathovagal balance in the control of heart rate. Studies showed a decrease in spectral energy in the low frequency (LF) band in case of fetal distress.

An extremely low LF power was a good predictor of severe fetal acidosis with a sensitivity of 97.5% and a specificity of 86.1%. The diagnostic value of spectral analysis to detect fetal acidosis seems promising. However, the number of acidotic fetuses in the included studies was too small to determine clinical applicability.

Also in 2008 a team with Pedro Pereira Rodrigues, Raquel Sebasti, and Cristina Costa Santos (7) presented a work with aim to extend the cardiotocography monitoring system with memory-less fading statistics in order to improve the detection of change of behavior and classifying apgar score. The relevance of fading statistics evolution for detecting changes of behavior in tracings and assess the relevance of fading statistics evolution in the prediction of newborn outcome through the apgar score at 1 and 5 minutes. A program for automated analysis of tracings, developed over the last 15 years in University of Porto, Omniview SisPorto, provides visual and sound alerts for non reassuring fetal state. However, it usually takes up to 10 min to trigger these alerts and so new methods are needed to improve the detection of non reassuring fetal state. Omniview-SisPorto system also provides the following quantitative parameters useful to medical interpretation of cardiotocograms and to subsequent clinical decision: the FHR baseline, the number of accelerations, the percentage of tracing with abnormal short-term variability (STV) and long-term variability (LTV) and the average STV and LTV. What distinguishes this work from earlier ones is automatic data feeds. We do not just have people who are entering information into a computer. Instead, we have computers entering data into each other. This is a significant approach. These tracings were acquired in four hospitals.
located in Portugal, Switzerland, Germany and Australia, in the context of a multicentre observational study. As traditionally targeted, we expect to identify in cardiotocograms tracings the non reassuring fetal state, predicting the newborn outcome, which is considered a bad newborn outcome when Apgar score measured 1 minute after the birth is under 7. Moreover, given the application of fading statistics as low-pass filter, we believe that the visualization of fading statistics evolution might in fact improve the physicians accuracy and agreement in the diagnosis.

In 2008 comes another work by Warrick that studies noise suppression for Intrapartum Cardiotocography to Discriminate Normal and Hypoxic Fetuses. The correlation approach used in that study is known to be susceptible to noise. This study was the attempt to reduce model noise by applying the pseudo inverse technique. The team constructed linear system-identification models of cardiotocography (CTG) data collected during labour and delivery. The models are the impulse response functions (IRFs) of the input-output system relating the uterine pressure (UP) stimulus to the fetal heart rate (FHR) response. Then they compare models obtained with and without applying noise suppression via the pseudo inverse technique. Finally, to determine the ability of the models to discriminate healthy from hypoxic fetuses, they use the average models as feature vectors of a support-vector-machine (SVM) classifier. The database consisted of 161 intrapartum CTG tracings (762 hrs) for pregnancies having a birth gestational age greater than 36 weeks and having no known genetic malformations.

The results without pseudo inverse included significant noise; applying the pseudo inverse resulted in cleaner models. The low VAF values in general are not unexpected since UP is not the sole influence on FHR. The reduction in VAF using pseudo inverse is likely indicative of reduced overfitting, that information was also preserved by this noise suppression is confirmed by the similar discrimination of both models. This similarity can also be explained by the fact that the final model decimation results in IRFs with similar low-pass energy. While time averaging also improves the model signal to noise ratio, the cleaner pseudo-inverse models may be preferable short-term estimates.
In 2009 a new team consisted of Manuela Ferrario Z Maria G. Signorini Z Giovanni Magenes presented a work that had as a main goal to suggest new indices for a correct identification of the intrauterine growth-restricted (IUGR) fetuses on the basis of fetal heart rate (FHR) variability analysis performed in the antepartum period. The term (IUGR) describes a decrease in fetal growth rate that prevents a fetus from obtaining his or her complete growth potential. The fetus is at risk of hypoxia and this condition is often associated with increased mortality and morbidity. The recent imaging ultrasound technology permits to assess with high resolution the fetal biometry. The comparison with population standards can thus identify the small-for-gestational-age (SGA) fetuses, characterized by biometric dimensions. Unfortunately, this group includes healthy fetuses of small size as well. A crucial problem in fetal monitoring is therefore to decide if the small dimensions are physiological or due to a pathological condition. On one side, anticipating the delivery time and removing the fetus from a suboptimal environment can prevent risk of significant morbidities. On the other hand, the risk of intrauterine compromise has to be weighted against potential risks from iatrogenic premature delivery, which are typically higher before the 32nd –34th gestational week. Beginning at the gestational age of 27 weeks, the probability of survival is increased by 1% for every further day of permanence of the fetus in uterus. Thus, it is crucial to accurately determine the real condition of the fetus in order to avoid an unnecessary caesarean section. The fetuses were selected by considering three groups: normal, severe IUGR and not severe IUGR. The normal group includes 17 fetuses without pathologies, delivered at term by spontaneous labor and having a good Apgar score. The severe IUGR group comprises 23 small fetuses, prematurely delivered by a caesarean section (before the 34th gestational week) because of the appearance of life-threatening conditions. The not severe IUGR group includes 19 small fetuses delivered after the 34th gestational week and classified as IUGR at delivery by clinicians. For this group, we supposed that they were only small-for-gestational-age fetuses. As reported in several review studies, the indices commonly adopted in CTG analysis are poorly suitable for a clinical directive. Thus, more advanced analysis techniques were adopted and an attempt of a multiparametric approach was performed. This analyses included the computation of Lempel Ziv complexity (LZC)
index and the multiscale entropy (MSE) estimation. In addition, a preliminary k-mean cluster analysis was carried out to show the separability of IUGRs from physiological fetuses on the basis of the computed indices. The results were sensitivity and accuracy (Se = 77.8%, Ac = 82.4%). The results show the proposed LZC and the MSE could be useful to identify the actual IUGRs and to separate them from the physiological fetuses, providing good values of sensitivity and accuracy. The work of the team (Wajid Aziz, Taher Biala, Federico Cardona Rocha, Michael Wailoo, Fernando S. Schlindwein.) in 2010 shows an association of intrauterine growth restriction (IUGR) with an increased risk of cardiovascular disease in later life. The non-optimal fetal growth may alter the development of the ANS and this appears to persist in later life. The aim of the present work is to analyse the synergic activity of the ANS in normal and growth restricted children. For that purpose, heart rate variability analysis from 24 hour ECG recordings of 70 children between 9 and 10 years old, normal and IUGR was performed using linear and non-linear time series analysis techniques. The HRV parameters showed no significant difference between normal and IUGR children. Low birth weight and its association with development of the cardiovascular system and its control have been extensively studied. In order to investigate the effect of low birth weight on HRV parameters, the IUGR children were further divided into two groups: IUGR-1 (birth weight < 2.50 kg) and IUGR-2 (birth weight ≥ 2.50 kg). The results demonstrated that most of the HRV measures showed significant differences between normal Vs. IUGR-1 as well as IUGR-1 Vs. IUGR-2 groups. The effect of gender on HRV measures were also examined and we noticed that girls had lower HRV than boys. In this study, both linear (time and frequency domains) and nonlinear HRV parameters were analysed.

I included this work in my survey as an example of the effect of problems during labor after 10 years of life. Children with a combination of low birth weight and relatively high BMI had a cardiac risk of 44%. Finds indicate that disturbances in ANS function reflected by reduced heart rate variability may represent one of the pathways to negative outcome of the cardiovascular system and hence the risk of coronary heart disease in low birth weight IUGR children. By any criterion, IUGR children do not
catch up with normal children in height or weight in the first decade of their life. This team will repeat the work in the second decade of the same children.

Also in 2010 P. Abry, H. Helgason, P. Goncalv`es, E. Pereira, P. Gaucherand, M. Doret gave released a work that tries to examine the benefits of using multifractal analysis for studying the FHR variability and identifying healthy and unhealthy fetus. To do so, the wavelet leader multifractal analysis was applied to a remarkable intrapartum F-ECG set of data, collected within the Hopital Femme-M`ere-Enfant academic hospital in Lyon, France. More precisely, the aims was: i) assessing whether FHR variability can be fruitfully characterized by multifractal attributes, ii) testing whether such multifractal attributes can provide a robust and significant discrimination between healthy and unhealthy fetus, and iii) evaluating the range of time before delivery within which such a discrimination can be performed. A wavelet Leader based multifractal analysis has been applied to three classes of FHR time series, corresponding respectively to correctly diagnosed healthy (TN) non-healthy (TP) and incorrectly diagnosed as non-healthy (FP) fetus. It has been shown i) that the variability in fetal FHR can be satisfactorily characterized by the wavelet Leaders multifractal analysis, even when applied to 15min long only time windows; ii) that a statistically significant discrimination between TN and TP, but also, and mostly, between FP and TP, can be achieved using MF attributes. iii) that this discrimination can be obtained much earlier than the last 15min, 15min being the typical range of time within which a decision is to be made in practice. These results are promising as they open the track for the use of multifractal analysis to reduce the number of unnecessary c-sections. Multifractal analysis, being practically based mostly on a discrete wavelet transform, allows for on-line investigations and real-time implementations.

In 2010 a Greek team again consisted of Argyro Kampouraki, George Manis, and Christophoros Nikou, shows the potential benefit of using support vector machine (SVM) learning to classify heart rate signals. Support vector classifiers are based on recent advances in statistical learning theory. They use a hypothesis space of linear functions in a high-dimensional feature space, trained with a learning algorithm from optimization theory that implements a learning bias derived from statistical learning
theory. In the last decade, SVM learning has found a wide range of applications. Support vector learning strategy is a principled and very powerful method that has outperformed most other systems in a wide variety of applications. The learning machine is given a training set of examples (or inputs), belonging to two classes, with associated labels (or output values). The examples are in form of attribute vectors and the SVM finds the hyperplane separating the input data and being furthest from both convex hulls. If the data are not linearly separable, a set of slack variables is introduced representing the amount by which the linear constraint is violated by each data point.

In this study, heartbeat time series are classified using support vector machines (SVMs). Statistical methods and signal analysis techniques are used to extract features from the signals. The SVM classifier is favorably compared to other neural network-based classification approaches by performing leave-one-out cross validation. The performance of the SVM with respect to other state-of-the-art classifiers is also confirmed by the classification of signals presenting very low signal-to-noise ratio. This work of course refers to HRV analysis in adults but gives an analytical way of how the way SVM work in the FHR analysis also and that’s the reason it’s significant to our presentation.

In the work in 2010 of, (Vaclav Chudacek, Michal Huptych, George Georgoulas, Lenka Lhotska, Chrysostomos Stylios, Michal Koucky, Petr Janku) an almost complete set of features previously used for FHR description is investigated and the features are assessed based on their statistical significance in the task of distinguishing the records into three FIGO classes. All recordings were checked for patient anamnesis and only one fold pregnancies delivered during 38th – 42nd week of pregnancy were chosen for the final database, which consisted of 613 delivery recordings altogether. For the evaluation in this work expert annotation was used. This has its drawbacks – it is much more subjective, and suffers from inter- and intra-observer variations but it gives better insight into the real clinical decision making than the postdelivery scores based on pH or overall newborn behavior, as described by Apgar score. Preprocessing process consisted of four main steps: segment selection, artifacts removal, interpolation and signal detrend. Segments were
selected from the complete recordings, some of them up to 12 hours long, as close as possible to the actual delivery. Signal quality was evaluated in relation to the segment position and the segment with the best score was selected. Segments were maximally 24 minutes long and due to further preprocessing (gap interpolation, noisy segments removal) were truncated to 20 minutes long segments – 4800 samples when using 4 Hz sampling frequency. The algorithm was utilized for artefact removal and cubic hermite spline interpolation. Then the signal was decomposed into five levels using the algorithm with (db4) mother wavelet. Based on the decomposition of the signal the mean and standard deviation was computed, and other statistical parameters in all detail. In the next step nonlinear known methods from adult HRV research were used such as: Higuchi’s Fractal dimension; Correlation dimension; Approximate Entropy (ApEn); Sample Entropy (SampEn); Lempel Ziv Complexity (LZC). Three different feature selection techniques were used to rank the features based on their performance in the potential classification process using 10-fold cross-validation. Based on previous experience the following techniques gave results – each one based on slightly different principle. Information Gain Evaluation (InfoGain) evaluates attributes by measuring their information gain with respect to the class. One Rule Evaluation uses the simple minimum-error measure adopted by the One Rule classifier. SVM Feature Evaluation evaluates attributes using recursive feature elimination with a linear support vector machine. Appropriate statistical tests against the expert annotation were used. The inter-correlation of the nonlinear features were in the range of 0.53-0.86 – therefore it did not fulfilled the condition for “high” correlation (above 0.90). In this work we see 2 new thinks for discussion. The first is the comparison of all the known nonlinear methods with statistics and the second is the statistical assessment of the features on large dataset against expert annotation.

In the work of (Philip A. Warrick, Emily F. Hamilton, Robert E. Kearney, Doina Precup) in 2010 we have a presentation of a novel approach to classifying normal and hypoxic fetuses during labor, using a mixture of system identification and machine learning methods. Uterine pressure (UP) from contractions is the input and the fetal heart rate (FHR) as an output, and fit a non-parametric linear model describing their
relationship. Special steps were taken to deal with noise and guard against overfitting in this step. This model inherently contains information about the strength and timing of the FHR response to contractions, in contrast to the feature detection approach where these relations must be explicitly computed as amplitude ratios and time delays, respectively. Based on these models, we create a set of attributes which are then used to classify the fetal state, using decision trees. Database consisted of 264 intrapartum CTG recordings for pregnancies having a birth gestational age greater than 36 weeks and no known genetic malformations. The accuracy for the normal class is very high, consistently above 90%. This performance is significantly better than that obtained previously using feature-based methods. The accuracy of the pathological class was much lower, around 50% but in the same cases the accuracy from clinicians was 30%. In this paper, the difference is the use of system identification methods, instead of feature extraction, as a pre-processing step. This is a fully automated procedure, which can easily be deployed with the software associated with current CTG monitors which are in clinical use. This makes this approach unique among the state-of-art methods in this subfield. Given the fact that many birth-related brain injury cases could have been prevented by correct CTG interpretation, these results indicate that system identification and machine learning approach could be very helpful for this challenging diagnostic problem, and in particular, that it could help clinicians diagnose problematic cases earlier. The primary aim of the next study (Diogo Ayres-de-Campos, Austin Ugwumadu, Philip Banfield, Pauline Lynch, Pina Amin, David Horwell, Antonia Costa, Cristina Santos, João Bernardes) in 2010 was to determine whether computer analysis of intrapartum fetal monitoring signals with real-time alerts will reduce the rate of umbilical artery metabolic acidosis compared to continuous electronic fetal monitoring as previously performed. Secondary aims are to quantify other measures of perinatal outcome, intervention rates and signal quality measures in both arms of the study. This is a pragmatic multicentre randomised clinical trial, to be carried out in five United Kingdom hospitals, with high-risk women in labour women aged ≥ 16 years, able to provide written informed consent, singleton pregnancies ≥ 36 weeks, cephalic presentation, no known major fetal malformations, in labour but excluding active second stage, planned for continuous CTG monitoring, and no known contra-
indication for vaginal delivery. Eligible women were randomised using a computer-generated randomisation sequence to one of the two arms: continuous computer analysis of fetal monitoring signals with real-time alerts (intervention arm) or continuous CTG monitoring as previously performed (control arm).

Electrocardiographic monitoring and fetal scalp blood sampling will be available in both arms. The primary outcome measure is the incidence of fetal metabolic acidosis (umbilical artery pH < 7.05, cord arterial base deficit > 12 mmol/L). Secondary outcome measures are: caesarean section and instrumental vaginal delivery rates, use of fetal blood sampling, 5-minute Apgar score < 7, neonatal intensive care unit admission, moderate and severe neonatal encephalopathy with a marker of hypoxia, perinatal death, rate of internal monitoring, tracing quality, and signal loss. Analysis will follow an intention to treat principle. Incidences of primary and secondary outcomes were compared between groups. Assuming a reduction in metabolic acidosis from 2.8% to 1.8%, using a two-sided test and 10% loss to follow-up, 8000 women need to be randomised. This study provides evidence of the impact of intrapartum monitoring with computer analysis and real-time alerts on the incidence of adverse perinatal outcomes, intrapartum interventions and signal quality. In the context by (H. Helgason, P. Abry, P. Goncalves, Cl. Gharib, P. Gaucherand, and M. Doret) 2011 comes an interesting proposing of a novel approach for measuring the complexity of FHR data, extracted from the computation of a family of (near-continuous piecewise linear) approximations of FHR data. The originality of the proposed method stems from the fact that it renews classical trend versus variability heart rate analysis in the following respect: 1) It is multiscale (allows for nonuniform time-resolution) and adaptive (data driven), two key properties that efficiently address the nonstationary and widely varying nature of per partum FHR; and 2) It jointly analyzes trend and variability. Moreover, the method is originally grounded on a network flow algorithm enabling fast computations of the proposed per partum FHR approximations. The method is then applied to a collection of real per partum FHR time series, carefully constituted by obstetricians. 47 cases split the available database into three groups by combining the a posteriori information related to the fetus health status to the a priori FHR pattern classification: 15 healthy fetuses,
normal FHR pattern; 17 healthy fetuses, abnormal FHR pattern; 15 unhealthy fetuses, abnormal FHR pattern. In this study using only linear methods (a MATLAB algorithm) were used and we have an attempt to solve the problem of very low specificity (high False Positive rate) which is often when using linear methods. The high sensitivity (high True Positive rate) is crucial but the appearance of high False Positive fetuses results in a significant number of unnecessary operative deliveries (instrumental delivery, caesarean) performed for fetuses showing at birth, hence a posteriori, no sign of asphyxia.

In the next work (Spilkaa, V. Chudáceka, M. Kouck, L. Lhotska, M. Huptycha, P. Jank, G. Georgoulas, C. Stylios) in 2011 the database contained 217 recordings. Arterial pH values were available for all records and, based on pH threshold, 94 were considered as pathological (the neonatal acidemia is defined as pH below 7.05). For comparison the expert annotations were gathered, using an in-house developed annotation system, from three experts in the field of obstetrics. To be able to compare the results to those of clinical praxis computed the morphological features introduced by the FIGO. Preprocessing consisted of three main steps: segment selection, artefacts removal and interpolation. A number of nonlinear methods for FHR analysis was used afterwards. The measure of fractal dimension was performed. Another attempt was to measure the length of FHR curve using the Higuchi method. Probably the most successful nonlinear methods for FHR analysis such as approximate entropy (ApEn), ansample entropy (SampEn), and Lempel Ziv (LZC) were also tried. The selected data were graded with 0 for normal class and with 1 for pathological class.

Again the comparison of modern nonlinear methods provides better results. The discrimination between normal and pathological examples is most apparent for features SampEn, and LZC. When the nonlinear features were excluded and only conventional features were used the classification performance decreased.

In the paper of (Nirajana K., Mohd Ali MA, Edmond Zahedi, Shuhaila Ahmed, Fauziah M. Hassan) in 2011 presented a new approach for FHR feature extraction based on empirical mode decomposition (EMD) is proposed which was used along with support vector machine (SVM) for the classification of FHR as normal or at risk. The FHR were recorded from subjects and the dataset consist of 90 randomly selected
records. All records were labelled as normal or at risk by 2 expert obstetricians. The standard deviation of the EMD components are input as features to a SVM to classify FHR samples. EMD is a method to decompose non linear and non stationary into several monotonic components as intrinsic mode functions. The most appealing nature of EMD is its dependency on the data driven mechanism which does not require a priori known basis unlike Wavelet and Fourier transform. Then SVM has as a main goal to construct an optimal hyperplane as the decision surface in such way that the margin of separation between the closest data points belonging to different classes is minimized. SVM is based on the principle of structural risk minimization method. The 5 fold cross validation test gave an accuracy of 86% and the sensitivity was 94,8%. The proposed methodology is a promising new approach specially for the classification of FHR signals. It has different approach from other methods so the comparison is difficult. The results are quit promising but the data set was small. We have also only 2 class labels to consider and the extension in multi class classification is appropriate. The association of the FHR classification with apgar score is also recommended for future work.

The paper of (R. Czabanski, J. Jezewski , A. Matonia , M. Jezewski) in 2012 presented a new method for assessing the risk of neonatal acidemia, which was based on two-step parametric analysis of fetal heart rate signal. In the first step, the quantitative parameters of signals are classified using fuzzy methods, where the rule bases of the fuzzy systems (the integration of neural networks and fuzzy models constitutes so called neuro-fuzzy systems), They are defined on the basis of guidelines for electronic fetal monitoring from International Federation of Gynecology and Obstetrics. (I described them in my introduction, according to FIGO guidelines the FHR recording can be assign to one of three classes, describing the fetal state as “normal”, “suspicious” or “pathological”). The goal of the fuzzy classification is to confirm the fetal wellbeing with the highest degree of certainty. The fuzzy assessment of the fetal state corresponds to the screening procedure, whose goal is to eliminate healthy patients from further diagnostic. In the second step of classification, the FHR signal descriptive parameters are assessed with multilayer perceptron and Lagrangian Support Vector Machines (LSVM) classifiers. However,
only the recordings which in the first step of the analysis were assessed as indicating the abnormal fetal state are classified nonlinearly. The research material consisted of quantitative parameters describing fetal heart rate signals obtained form the archive of computerized fetal surveillance system.

The combination of the WFSS and the LSVM approaches provided the best classification results (QI = 88.2%, CC = 92.0%). In all cases, the two-step evaluation of the FHR recordings resulted in increasing the classification sensitivity. The increase in sensitivity was usually accompanied by a decrease in specificity, however the final classification quality improvement measured with QI was noticed. For the analyzed database the number of fetuses, characterized by the risk of hypoxia was less than 14% of all cases.

**B. Discussion-criticism of previous works**

Unfortunately, there is no other noninvasive diagnostic method that would be able to play the role of the reference evaluating the actual fetal state with higher certainty and accuracy at the time of fetal monitoring. However there are many points of criticism in the interpretation of cardiotocograms that lead to considerable such as:

1. Insufficient understanding of the (patho-)physiological background
2. Too indirect signal of the foetal condition
3. Number of technical pitfalls
4. Differences in recording techniques
5. Lack of uniform classification systems
6. Substantial intra- and inter-observer variation regarding the interpretation
7. Low validity, high incidence of false-positive findings
8. Leads to an increase in artificial deliveries

Real fetal state will be known only just after the delivery. However, it is assumed that the fetal state can not change rapidly during pregnancy and therefore, the retro-spective analysis can be applied in the reviewing process. It involves the assignment of the fetal outcome to fetal state at the time of FHR signal acquisition. Also a reverse process is possible, when the prediction of fetal outcome is made on
the basis of the classification result of the recorded FHR signal. Although this approach is not entirely correct (as for example, the newborn state may deteriorate due to some erroneous medical procedures during delivery) nevertheless, it remains the most objective reference method to evaluate the algorithms for qualitative assessment of the fetal state. The reference fetal outcome is assessed by clinicians after delivery with a help of three main attributes of the newborn: percentile of birth weight, Apgar score (representing the result of a subjective, visual assessment of the newborn) and measurement of the negative logarithm of hydronium ion activity (pH) in the umbilical cord vein blood. Low pH indicates an inadequate respiratory gas pressure in the blood of newborns and provides an objective sign of fetal hypoxia. The value of pH >7.20 indicates the fetal wellbeing, while pH < 7.10 means an abnormal fetal state. Values in between are usually interpreted as the possibility of fetal health risk. However it is known that babies with severe acidosis (pH 7.0 or less) will subsequently be normal in a percentage of 90%.

More accurate interpretation of the FHR monitoring, the use of foetal scalp blood pH monitoring, and possibly, the use of acoustic or scalp stimulation to elicit FHR accelerations, can lead to more precise diagnosis of the condition of the foetus and, by inference, may lead to a decrease in the surgical intervention rate.

In general we see that linear methods offers high sensitivity (High true positive rate) but also result in a significant number of unnecessary caesareans (High false positive). The non linear filters in the last 5 years seem to solve the problem. The data reduction and multiple filters better resaults and give high specificity (Low false positive). Comparison of cardiotography with experts tilted in favour of cardiotography. Red alert systems in most of countries give extra help to gynecologists and the decision nowadays is not entirely to the doctor.
C. Proposed Algorithm
The block diagram of the proposed algorithm is presented in Figure...

![Diagram of the proposed algorithm]

**Figure 4.1** Block Diagram of the proposed algorithm

**Noise Reduction Procedure**
Noise is compounded with artifacts (brought by maternal or foetal movement) (Keith & Smith, 1986). Another important cause of noise is the loss of contact of the transducer due to critical conditions occur during labour (Figure 4.2).
The removal of noise proved to be a difficult task. According to Mongeli (1997) every FHR value above 240 and below 30 bpm is considered noise and it is excluded from analysis. The use of thresholding with ranges (30 – 240, Mongeli 1997), (60 – 200, Dawes, 1982) proved to be insufficient. Dawes (1990) proposed noise detection by using the 1\textsuperscript{st} derivative. The definition of the noise given by him is any abrupt fall in FHR equivalent to >35 bpm followed by abrupt rises attributed to transient detection of the maternal pulse. If within the next 10 min after the abrupt fall there was a corresponding abrupt rise >35 bpm, then the intervening section was treated as erroneous (as an episode of signal loss).

By using only the 1\textsuperscript{st} derivative in the previous 'noise' area the only FHR 'noise' samples the algorithm is going to detect are those which are near any abrupt fall. A standalone use of the 1\textsuperscript{st} derivative therefore can't detect 'noise' values which are not occurring rapidly and their abrupt fall is not followed by abrupt rise close to the normal signal (before the abrupt fall), as Dawes (1990) assumes. This limitation is the cause for all the underlined values (68 70 58) not to be considered as noise.

Mantel (1990) in order to increase the detection of FHR variability changed the mean value of the R-R intervals used for the calculation of every FHR value to 2.5 seconds. Any attempt to calculate a FHR value by using the mean of R-R intervals and not any R-R interval separately is a cause for loss of FHR variability and useful information. The fact that Dawes (1990) and Mantel (1990) created algorithms for antenatal use where FHR beat to beat variability is absent does not reduce the limitation of their methods. Mongeli (1997) and Chung (1995), although they apply their algorithm in FHR traces during labour, sample the FHR values every 2 seconds and 10 seconds.
intervals respectively. The noise removal procedure, which is proposed in this thesis, is presented in the flow diagram below (Figure 4.3).

![Block diagram of the Noise removal procedure](image)

**Figure 4.3** Block diagram of the Noise removal procedure

The detection of the noise uses a combination of minimum and maximum thresholding and the 1st derivative by checking the sign and the amplitude of the gradient. The thresholding used is any value below 40 and above 240 considered to be noise. The amplitude of the gradient is set at 35 bpm, as Dawes (1990). The sign of the gradient is used for the detection of the start and the end of any noise area. In order to eliminate any possibility for considering noise as normal values the algorithm goes back and forward 5 samples (2.5-sec) in every value outside the [40 240] range and marks the area considering it as part of the 'noise' area. Also whenever there is a negative gradient greater than 35 bpm in the FHR trace from one point to the next, which means that there is an abrupt fall in the FHR signal, the algorithm considers the next five samples part of the 'noise' area too. Everytime there is a positive gradient above 35 bpm, which means that possibly the 'noise' area is ending at the particular point, the algorithm considers the previous 5 samples as part of the 'noise' area.
Figure 4.4. An example of noise detection. In case B the red area is the 'noise' area.

In FHR signal the discarding of a value which is considered to be noise must be followed by immediate replacement with another value close to them before and after the discarded one. So the signal is linearly interpolated between the values A,B as the below equation presents:

$$ FHR_{j=1...N} = FHR_A + \frac{(FHR_B - FHR_A)*j}{N+1} $$

Two examples showing the noise removal procedure are presented in the figures 4.5, 4.6.

Figure 4.5 An example of the noise removal procedure

Although the FHR signal consists of excessive noise the removal noise procedure succeeds to create a noiseless FHR signal for further processing.
Figure 4.6 An example of the removal of noise procedure

The procedure of the noise removal is done for each segment the user is testing. This is very important since it can be used during real-time conditions. At the beginning of the recording, the algorithm waits for a period before processing the FHR data (up to 20 –25 min). By the time the desirable number of samples is gathered, the removal of noise, the estimation of the FHR baseline, and the feature extraction following the noise removal procedure can be applied. The whole procedure can be updated every five or ten minutes i.e. 0-25, 5 – 30,

FEATURE EXTRACTION OF THE CTG SIGNAL PROPERTIES

The CTG signal properties are:

- FHR baseline
- FHR variability
- Accelerations
- Decelerations

CALCULATION OF THE FHR BASELINE

The FHR baseline derived from the proposed algorithm is an array superimposed on the FHR signal. The mean value of that array was regarded as the FHR baseline value for the FHR segment presented.
The block diagram of the proposed algorithm for FHR baseline extraction is depicted in figure 4.7

Figure 4.7 FHR baseline extraction algorithm

The wavelet decomposition of the FHR signal is presented in figure 4.8.
Figure 4.8 Wavelet decomposition of the FHR signal

From the wavelet coefficients across scales the local maxima are computed in order to acquire the multiscale edge representation (Figure 4.9)

Figure 4.9 Multiscale edge representation of the FHR signal. The red stars are the local maxima across scales of the wavelet coefficients.

The next step of the proposed algorithm is clustering of the local maxima within each scale. The initial centers for the two classes were the mean value of coefficients that represented the normal signal (close to zero) and the mean value of coefficients that correspond to large local maxima (70th percentile). After the clustering procedure
the removal of coefficients that correspond to second cluster is made in order to remove the fluctuations of the FHR signal and acquire the baseline. Then after the inverse wavelet transform the FHR baseline is extracted (Figure 4.10)

![FHR baseline extraction](image)

**Figure 4.10** FHR baseline extraction

### CALCULATION OF FHR VARIABILITY

According to FIGO (1987) FHR variability is the amplitude of the oscillations around the FHR baseline. The calculation of the standard deviation leads only to the calculation of a value which is not the variability of the signal. An approximation has been done to fulfil FIGO (1987) definition, therefore the FHR variability was regarded as twice the standard deviation multiplied by the square root of 2. The FHR variability of each FHR signals when acceleration and decelerations being absent was calculated using the below equation:

$$SD_{in\_N} = 2\sqrt{\frac{\sum_{i=1}^{N} (FHRi - BASELNEi)^2}{N-1}}$$

The mean value of the standard deviation array was regarded the FHR variability value for the FHR segment tested.

### IDENTIFICATION OF ACCELERATIONS

The identification of accelerations with the agreement of the collaborating doctors was based on FIGO (1987) definition. According to FIGO (1987) accelerations occur when the FHR signal is 10-15 bpm greater than FHR baseline for 10-15 seconds or more. In order for the algorithm to identify acceleration, with the use of internal counter, checks if the increase of the FHR is more than 15 bpm and it stays at this level for more than 15 seconds. An example of identification of acceleration is presented in Figure 4.11.
IDENTIFICATION AND CLASSIFICATION OF DECELERATIONS

The identification of decelerations with the agreement of the collaborating doctors was also based on the FIGO (1987) definition. A deceleration occurs when the FHR signal is 10 bpm less than the FHR baseline for 15 seconds or more. In this case the identification and classification is more complicated because the clinical analysis requires the detection not only of each deceleration but also the type of the particular deceleration. In order for the algorithm to identify deceleration, the use of internal counter checks if the decrease of the FHR is more than 10 bpm and it stays at this level for more than 15 seconds. An example of identification of deceleration is presented in Figure 4.12.

Figure 4.11 Identification of an acceleration, marked as A

Figure 4.12 Identification of a deceleration, marked as D
D. Quantitative Results

The twenty four segments of CTG trace, each lasting 25 minutes, were reviewed independently by a panel of seven experienced observers to interpret FHR baseline, the number of accelerations and the number and type of decelerations. FHR variability was categorized as normal or reduced (less than 5 beats per minute) according to FIGO (1987) definition. The observers were all senior obstetric staff (consultants or senior specialist registrars) who was actively involved with intrapartum clinical practice. The computer analyzed the same segments. Inter -observer agreement and agreement between observers and computer was determined using interclass correlation coefficient (ICC) for continuous variables: the FHR baseline, number of accelerations and the number of decelerations. The weighted K (kappa) coefficient was calculated for the dichotomous variable i.e. baseline variability (Taylor, 1999). These statistic variables have been used in previous publications concerning the CTG interpretation. Mongeli (1997) used the interclass correlation (ICC) as a measurement of agreement between the computer and the observers. Keith (1995), Cagnon (1993) and Bernades (1996) used the kappa coefficient in order to calculate intra and inter - observer variability.

The interclass correlation is a statistical variable used to describe the strength of the relationship between two variables. It is a number between −1 and +1 that measures how closely a set of data points tends to cluster about the regression line (best fitting line). If the correlation is close to +1, then the variables have a strong positive relationship. If it is close to −1, then there exist a strong negative relationship. If it is near 0, then little or no relationship exists. One way to calculate the correlation coefficient is to divide the covariance of X and Y by the product of the standard deviation of X and the standard deviation of Y. If X is one set of data points and Y another one, the covariance which, measures how much two variables change with respect to one another, is calculated from averaging the sum of the products of the deviation scores:

\[
\text{Covariance} = \frac{\sum_{i=1}^{N} (X_i - \text{Xmean}) \times (Y_i - \text{Ymean})}{N}
\]

where \( N \) is the number of data points.
The inter-observer agreement for the identification of decelerations is high (ICC = 0.93) and the inter-observer agreement for the classification of decelerations as late is satisfactory (ICC = 0.79). The agreement between the computer and the observers for the identification of decelerations was similarly high (ICC, 0.82 – 0.92). The agreement between the computer and the observers for the classification of decelerations as late is ranging from moderate (ICC = 0.68) to high (ICC = 0.85).

**Table 4.1.** Inter-observer agreement between experts (interclass correlation coefficients (ICC) for FHR baseline, accelerations and decelerations).

<table>
<thead>
<tr>
<th>CTG Features</th>
<th>Interclass Correlation Coefficients (ICC)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline FHR</td>
<td>0.93</td>
</tr>
<tr>
<td>Accelerations</td>
<td>0.27</td>
</tr>
<tr>
<td>Decelerations</td>
<td>0.93</td>
</tr>
<tr>
<td>Late Decelerations</td>
<td>0.79</td>
</tr>
</tbody>
</table>

Table 4.2 presents the agreement between observers and computer for the above CTG features.

**Table 4.2.** Agreement between observers and the computer (interclass correlation coefficients (ICC) for each CTG parameter)

<table>
<thead>
<tr>
<th>Observer</th>
<th>Baseline ICC</th>
<th>Accelerations ICC</th>
<th>Decelerations ICC</th>
<th>Late Decelerations ICC</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.95</td>
<td>0.41</td>
<td>0.92</td>
<td>0.85</td>
</tr>
<tr>
<td>2</td>
<td>0.94</td>
<td>0.72</td>
<td>0.86</td>
<td>0.82</td>
</tr>
<tr>
<td>3</td>
<td>0.98</td>
<td>0.74</td>
<td>0.87</td>
<td>0.81</td>
</tr>
<tr>
<td>4</td>
<td>0.94</td>
<td>0.80</td>
<td>0.91</td>
<td>0.73</td>
</tr>
<tr>
<td>5</td>
<td>0.94</td>
<td>0.06</td>
<td>0.88</td>
<td>0.77</td>
</tr>
<tr>
<td>6</td>
<td>0.95</td>
<td>0.72</td>
<td>0.82</td>
<td>0.68</td>
</tr>
<tr>
<td>7</td>
<td>0.91</td>
<td>0.18</td>
<td>0.87</td>
<td>0.74</td>
</tr>
</tbody>
</table>
REFERENCES


Borgatta L, Shrout PE and Divon MY. "Reliability and reproducibility of non-stress test readings” Am J Obstet Gynecol 1988;159: 554-558


Czabanski S, J. Jezewski, A. Matonia, M. Jezewski “Computerized analysis of fetal heart rate signals as the predictor of neonatal acidemia” Expert Systems with Applications February 2012 190:196


Diogo Ayres-de-Campos, Austin Ugwumadu, Philip Banfield, Pauline Lynch, “ A randomised clinical trial of intrapartum fetal monitoring with computer analysis and alerts versus previously available monitoring” BMC Pregnancy and Childbirth 2010 10:71


Grant J., M. "The foetal heart rate is normal, isn't it?" Lancet. 1991; 337: 215-218


Jezewski, A. Matonia, M. Jezewski. Cza "Computerized analysis of fetal heart rate signals as the predictor of neonatal academia." Expert Systems with Applications February 2012 1255:1270


Mongeli M, Dawkins R, Chung T, Sahota D, Jhon A.D. Spencer JAD, Chang AMZ. "Computerized estimation of the baseline foetal heart rate in labour, the low frequency line" Br J Obstet Gynaecol 1997; 104;1128 – 1133.


Kampouraki A., George Manis, and Christophoros Nikou "Heartbeat Time Series Classification With Support Vector Machines" Transactions on information technology in biomedicine, VOL. 13, July 2009 512:518


Spilkaa, V. Chudáceka, L. Lhotska, M. Huptycha, G. Georgoulas, C. Stylios "Using nonlinear features for fetal heart rate classification" Biomedical Signal Processing and Control BSPC-276; June 2011 653-661