Neural network applications in the field of electrocardiography

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By
M.G.T. Hut

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Neural Network Applications in the field of Electrocardiography.

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By

M.G.T. Hut

Student at the

Faculty of Mechanical Engineering

Eindhoven University of Technology

The Netherlands.

Summary.

A direct relationship between the amplitude of the R wave in lead V_1 of the electrocardiogram and the right venticular systolic pressure of the heart is suspected. A first attempt to determine this relationship accurately by applying a backpropagation neural network is described.

Izvod. **(Summary in Serbian)**

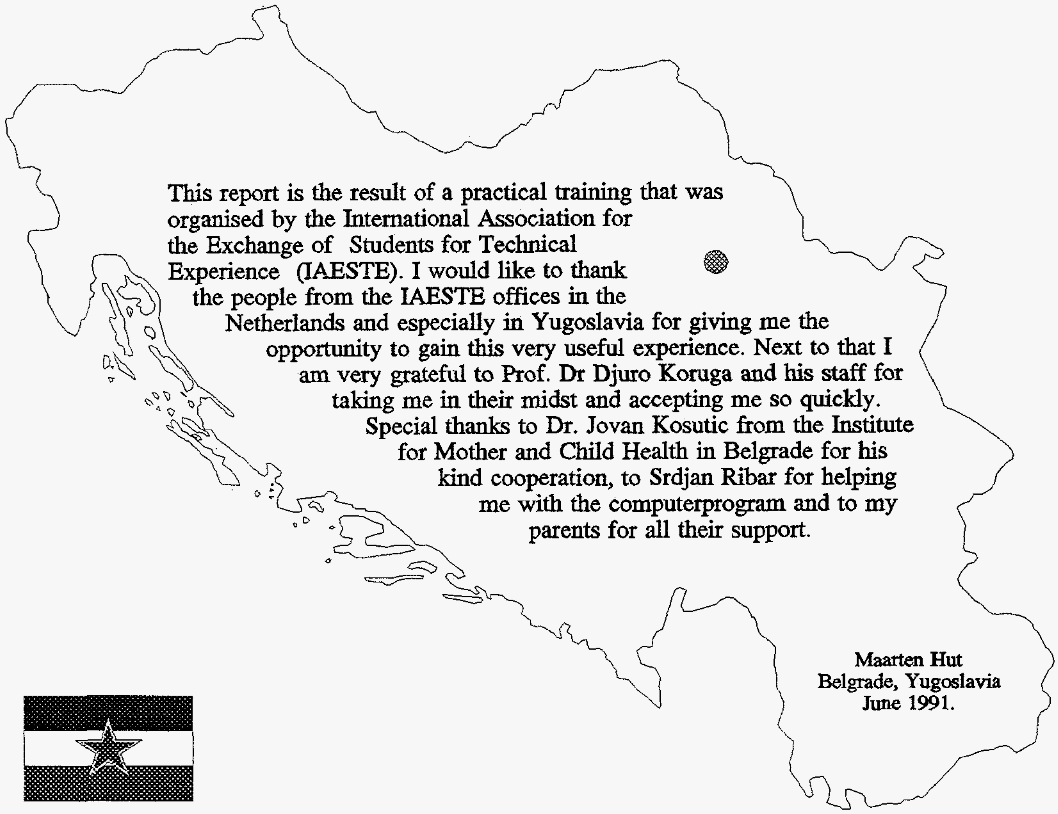
Pretpostavlja se da postoji neposredna veza izmedju R vrha u mernoj tački V_1 elektrokardiograma i sistolnog pritiska u desnoj komori srca.

U ovom radu je opisan prvi pokušaj odredjivanja ove veze uz promoć "backpropagation" zivčane mreže.

Samenvatting. (Summary in Dutch)

Er schijnt een direct verband tussen de amplitude van de R piek in meetpunt V_1 van het elektrocardiogram en de systolische druk in de rechter kamer van het hart te bestaan. Een eerste poging om deze relatie met behulp van een backpropagation neuraal netwerk te bepalen wordt beschreven.

General Information and Acknowledgements.



This report is the result of a practical training that was organised by the International Association for the Exchange of Students for Technical Experience (IAESTE). I would like to thank the people from the IAESTE offices in the Netherlands and especially in Yugoslavia for giving me the opportunity to gain this very useful experience. Next to that I am very grateful to Prof. Dr Djuro Koruga and his staff for taking me in their midst and accepting me so quickly. Special thanks to Dr. Jovan Kosutic from the Institute for Mother and Child Health in Belgrade for his kind cooperation, to Srdjan Ribar for helping me with the computerprogram and to my parents for all their support.

Maarten Hut
Belgrade, Yugoslavia
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Contents.

Chapter 1: Introduction.

Nowadays human cardiac activity can be monitored closely by recording the so-called electrocardiogram, which in simple terms is a plot of the electrical activationwave of the heart. Defects of the heart have often an influence on the appearance and shape of the electrocardiogram. A lot of cardiac diseases are known to affect the electrocardiogram in a certain way so they can be diagnosed earlier with the help of this non-invasive information source.

Some cardiac defects cause a big resistance in the outflow of the blood from the right ventricle. This means that the pressure in the ventricle increases. It is important that this pressure can be measured accurately. Until now this is done by using a quite invasive technique; a catheter is brought into the ventricle.

But maybe the electrocardiogram can also be helpful in this area, because in the past a relationship between one of the deflections of the electrocardiogram and the pressure in the right ventricle has been claimed several times.

This report describes a first attempt to determine a reliable relationship with the help of a quite new trend in computing techniques: *neurocomputing*[1]. A parallel information processing structure, called *neural network*, is applied to try to estimate the pressure in the right ventricle as a function of the electrocardiogram.

First neurocomputing and neural networks are described and an example which stresses the power of these new information processing systems compared to classical techniques is provided. In the following chapter the field of electrocardiography is introduced and the electrocardiogram as a diagnostic tool is further explored.

The final chapter desribes the experimental setup that was used to try to determine the relationship between electrocardiogram and pressure. Unfortunately no qualitative conclusions could be drawn so far, but the goal of this report is more to describe a first survey and maybe to provide necessities for the establishment of a basis around which a more successful experiment could be build up.

[1] Words or expressions printed in italics are explained in the glossary at page 35.

Chapter 2: Neurocomputing.

§ 2.1 Basics.

Human intelligence is partly based on the initial structure and organization of the brain. The human brain is build up as a network of nerve cells or neurons. Figure 1 shows a neuron that roughly consists of a nucleus, on long offshoot called axon and many short offshoots called dendrites.

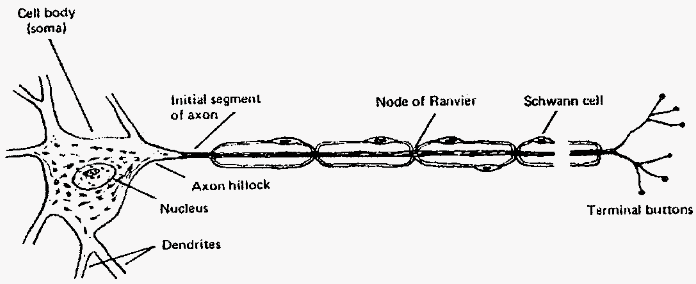

Figure 1
The structure of a nerve cell. Important parts are: the axon, the dendrites and the nucleus (Ganong, 1981: 29).

Each neuron receives its information in the form of electrical impulses via the dendrites. In the nucleus these pulses are added and if the resulting voltage exceeds a certain tresholdvalue it is sent via the axon. The axon transports the new pulse, multiplies it by a weightfactor and sends it to the next neuron. This way of information transmission has been the basis of an alternative to *programmed computing* and a new trend in information processing: neurocomputing.

To solve a problem using programmed computing requires at least an algorithm, a set of rules or a well specified function to be able to find a solution for the problem. Since computers operate on a totally logical basis, software has to be virtually perfect if it is to work.
Neurocomputing however is another approach to information processing that is based on transformations and that does not demand algorithm or rule development. Particularly in areas as pattern recognition, sensor processing and data analysis, where algorithms or rules are often hard to derive, this approach has already been applied successfully.

Formally, neurocomputing is the technological discipline concerned with parallel, distributed and adaptive information processing systems (such as neural networks) that develop information processing abilities in response to exposure to an information environment (Hecht-Nielsen, 1990: 2). In simple words this means the following: suppose that we want to know the value of a parameter that results from an unknown interaction of other parameters. when we have a statistically adequate set of training data (the known parameters that are supposed to be interacting) with solutions (the wanted parameters), then we can train a neural network with these data by supplying it with the correct output next to the input. The network can compare its output with the correct output and adapt itself if necessary. After the training is carried out properly, the network will be able to calculate unknown solutions belonging to other sets of similar data.

§ 2.2 Neural Networks.

As mentioned before, primary information processing systems of interest in the field of neurocomputing are neural networks.

The first major contribution to the development of neural networks as we know them today has been the invention of the *perceptron*[2]. The perceptron is a typical neural network structure that consists of one or more *processing elements* as shown in Figure 2. Training the perceptron takes place in the following way: the input is a (n+1)-dimensional vector $\vec{x} = (x_0, x_1, x_2, ..., x_n)$, where x_0 , which is called the bias input, is permanently set to 1. In the perceptron the input vector $\vec{x}$ is multiplied by the weight vector $\vec{w} = (w_0, w_1, w_2, ..., w_n)$. If the weighted sum $x_0w_0 + x_1w_1 + ... + x_nw_n \geq 0$ the output y' of the perceptron is 1, otherwise it is 0. The *weights* which are stored within the processing element are automatically

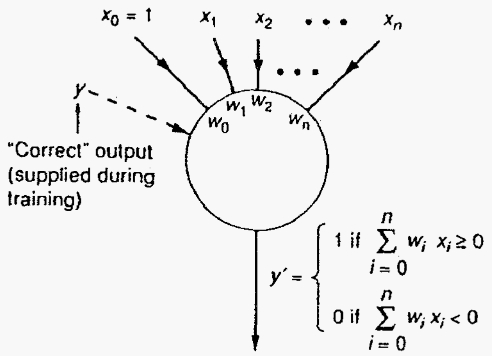

Figure 2
A single element perceptron (Hecht-Nielsen, 1990: 4).

[2] The perceptron: Classical neural network architecture which was invented in 1957 by Frank Rosenblatt who also wrote *Principles of Neurodynamics*, one of the first books on neurocomputing.

modified according to the perceptron *learning law* during the training process. This learning law adjusts the weight vector $\vec{w}$ in accordance with the equation

$$\vec{w}^{\,new} = \vec{w}^{\,old} + (y - y')\vec{x}, \tag{2.1}$$

where y' is the output of the perceptron and y is the desired correct output. It is obvious that the output error (y-y') = 0 if the output is correct, but if $y' \neq y$ the weights have to be altered so that the perceptron will tend not to make an error on this particular $\vec{x}$ vector again. This method of learning is called supervised training, because for each input $\vec{x}$ the correct input y was also supplied during training. Next to this type of training two other methods are in use: graded training[3] and self-organization[4].

At first neural networks were implemented and applicated for research rarely. Only when Very Large Scale Integration (VLSI) circuits became available neurocomputing became an accepted practical technology.
By definition a neural network is a parallel, distributed information processing structure consisting of processing elements (which can execute localized operations and have a local memory) placed in layers which are interconnected via unidirectional signal channels (so called connections). Each element can branch out into different connections all carrying the same output to another element in a different, or even in the same layer. The output signal of a processing element can be of any mathematical type (Hecht-Nielsen, 1990: 3). In Figure 3 a possible neural network structure is shown.
For various applications different network structures with different levels of complexity can be used. The most commonly used neural networks are: associative networks, mapping networks, spatiotemporal networks, stochastic and hierarchical networks. Describing all these different types of networks more specific would be interesting but not really relevant for the purpose of this report. For an extensive

[3] Graded training: The network does not receive desired outputs next to data inputs, but occasionally it is given a "grade" that informs the network about its overall performance since the last time it was graded.

[4] In self-organization training a network is only provided with data inputs and it has to organize itself into a useful configuration.

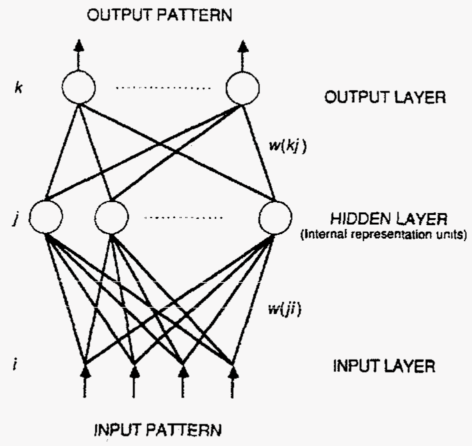

Figure 3
A possible neural network structure. All layers that are not connected to the periphery are called hidden layers (Pao, 1989: 121).

description of all types of networks the interested reader is referred to Hecht-Nielsen, 1990. The neural network that was used for this project which is a mapping neural network that operates according to the principle of backpropagation will be described next.

§ 2.3 The Backpropagation Neural Network.

§ 2.3.1 Architecture.

Mapping neural networks are networks that are especially applicable for numerical approximation of unknown mathematical functions $f : A \subset \mathbb{R}^n \rightarrow \mathbb{R}^m$ by means of training on examples (x_1,y_1), (x_2,y_2),...,(x_k,y_k),... where $y_k = f(x_k)$. A backpropagation neural network is a feature-based[5] mapping network. In Figure 4 its macroscopic architecture is shown. The *n* units in the first layer only accept and distribute the individual components x_i of the input vector $\vec{x}$. Every unit in each row receives the output of all units of the row below. The cumulative output of the *m* units of the final row is the network's approximation $\vec{y}'$ of the correct output $\vec{y}$. Next to these feedforward connections, each unit of every hidden row receives an error feedback connection from every unit in the layer above it.

[5] A feature network implements a functional input/output relationship that is expressed in terms of a general, modifiable functional form (≠*prototype network*)

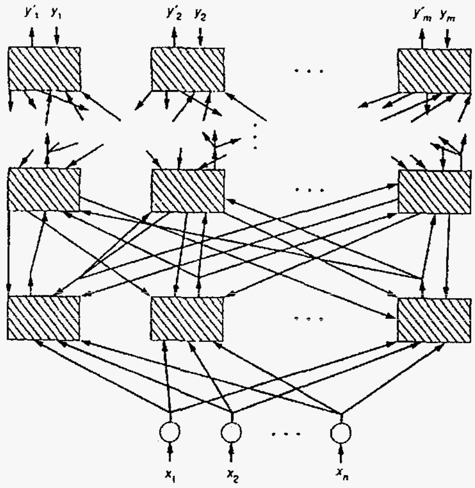

Figure 4
Macroscopic architecture of the backpropagation neural network. The input row and output row have n and m units; hidden rows have an arbitrary number of units (Hecht-Nielsen, 1990: 128)

§ 2.3.2 Operation.

This backpropagation gives the units the information they need to be able to adjust their weights. The mean squared error F that occurs in the estimation of the correct output is obviously a function of the weight vector $\vec{w}$ (Figure 5). Training the network means moving this vector in a direction so that the value of $F = F(\vec{w})$ will be smaller at the new value of $\vec{w}$ in the next iteration. The goal is to find the vector $\vec{w}$ that yields the minimal error F in a finite number of training trials. It is important that the number of training cycles on one training set stays limited, because if training is pushed too far overtraining occurs and the network becomes too specific (Figure 6).

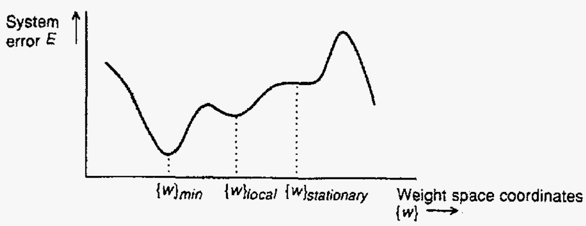

Figure 5
A one dimensional projection of a Q dimensional error surface; The error E $\equiv F$ as a function of the weightvector that has Q components (Pao: 1989, §5.3).

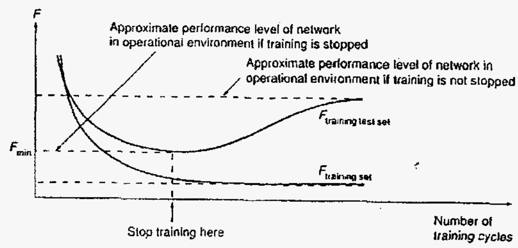

Figure 6
Training set error vs. training test set error; Overtraining occurs as the number of training cycles increases (Hecht-Nielsen: 1990, 117).

The backpropagation neural network uses the *generalized delta rule learning law* to modify the weightvector $\vec{w}$ so that $F(\vec{w})$ decreases.

This learning law operates in the following way:

Let

$$F_k = |f(\vec{x}_k) - \vec{y}'(\vec{x}_k,\vec{w})|^2 \tag{2.2}$$

be the square error made by the network on the k^{th} testing trial (with data set $(\vec{x}_k,\vec{y}_k) = (\vec{x}_k,f(\vec{x}_k))$). Then the mean squared error $F=F(\vec{w})$ is defined to be

$$F(\vec{w}) \equiv \lim_{n\to N}\frac{1}{n}\sum_{k=1}^{n} F_k \tag{1.3}$$

where N is the total number of training iterations.

The best way to minimize F is to move $\vec{w}$ in the direction in which the decrease of F is maximal. Assuming that F is differentiable, this direction is given by

$$-\nabla_{\vec{w}}F(\vec{w}) = -\left(\frac{\partial F}{\partial w_1},\frac{\partial F}{\partial w_2},\ldots,\frac{\partial F}{\partial w_Q}\right) \tag{2.4}$$

where Q is the number of components of $\vec{w}$.

Given an arbitrary weightvector $\vec{w}$, the weights have to be adjusted every iteration so that the weightvector moves in the above direction. The step that is taken every time should be small to prevent overshooting the minimum. When a minimum is reached, the gradient becomes zero and the weights keep their value in the subsequent iterations so that in fact training can be stopped. This process can be described by the following equation which is called the generalized delta rule learning law.

$$\vec{w}^{new} = \vec{w}^{old} - \alpha\nabla_{\vec{w}}F(\vec{w}) \tag{2.5}$$

Where $\alpha > 0$ is a small constant called the *learning rate.*

After the backpropagation neural network is trained according to this learning law on a satisfying set of training data the weights can be fixed and the network is ready for operation.

Although the development of this way of numerical approximation is not yet finished and notwithstanding the fact that there are still some assumptions to be justified many good results have already been achieved in this field.

An example of the possibilities is provided in the next section where the backpropagation approach is compared to the more classical method of adaptive filtering in a practical case.

§ 2.4 Backpropagation vs. Adaptive Filtering.

Systems that are very complex or time varying are often hard to be described by a precise signal model. When such a systems are also disturbed by noise, modelling or recovering the undisturbed signal becomes even more difficult. A classical method to remove unwanted noise from a complex signal is the use of adaptive filtering[5] techniques. In adaptive noise cancelling a reference signal which contains information about the noise process is usually available. This means that in this field the backpropagation neural network could also be applied successfully.
The practical example discussed here illustrates the power of neural networks compared to adaptive filters in the field of recovering interfered signals.

An important problem in registrating and analyzing the electrocardiogram (*ECG*; *see next chapter*) is the cancelling of mains frequency interference. In Figure 7 is shown how adaptive filters are used in the field of electrocardiography to remove noise from the ECG signal.
The adaptive filter only needs two variable weights to be able to estimate the magnitude and phase of the noise signal $z(t)$. Both of the weights should be applied to the reference signal, one directly and the other one shifted by 90°. When the noise signal is known, the undisturbed signal can be retrieved by adding $-z(t)$ to the recorded signal.

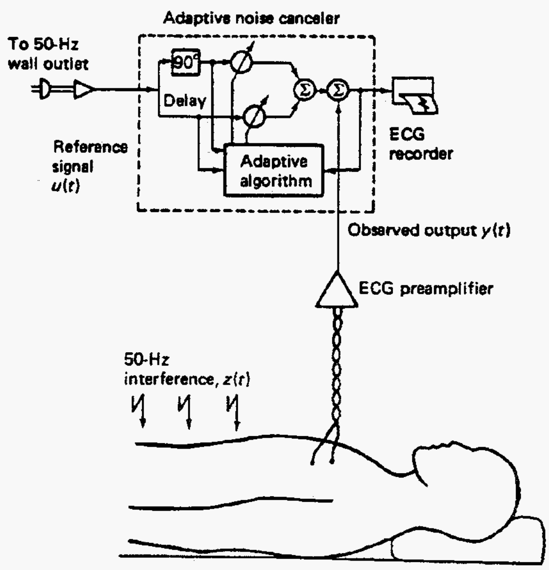

Figure 7
Adaptive filter set-up used for removing 50-Hz interference in ECG recording (Goodwin and Sin, 1984: 386).

[5] Although the field of adaptive filtering is very interesting, it will not be described extensively here. This chapter only serves as an illustration of the possibilities of backpropagation neural networks. The interested reader is referred to Goodwin and Sin, 1984.

Mathematically the ECG signal can be looked upon as a complex and time varying function and it is obvious that describing this function analytically will be very difficult. But as mentioned before we have the wanted signal at our disposal in this case, so an alternative to the classical adaptive filters to remove the noise is the use of a backpropagation neural network. That this approach can be very successful will appear from the following results of a computer-simulation.

First both a network and a filter are trained with an arbitrary signal called the desired signal y_1(t). A nuisance signal z(t) is added to y_1(t) resulting an input signal x(t) = y_1(t) + z(t). During training the network uses y_1(t) and the adaptive filter uses z(t) as reference. Figure 8 shows the performance of both techniques after 5120 iterations (with arbitrary initial weights). The upper two signals are the desired signal y_1(t) and the noisy signal z(t). The third signal is the networks output y_1'(t) and the fourth signal is the output of the filter y_1''(t).

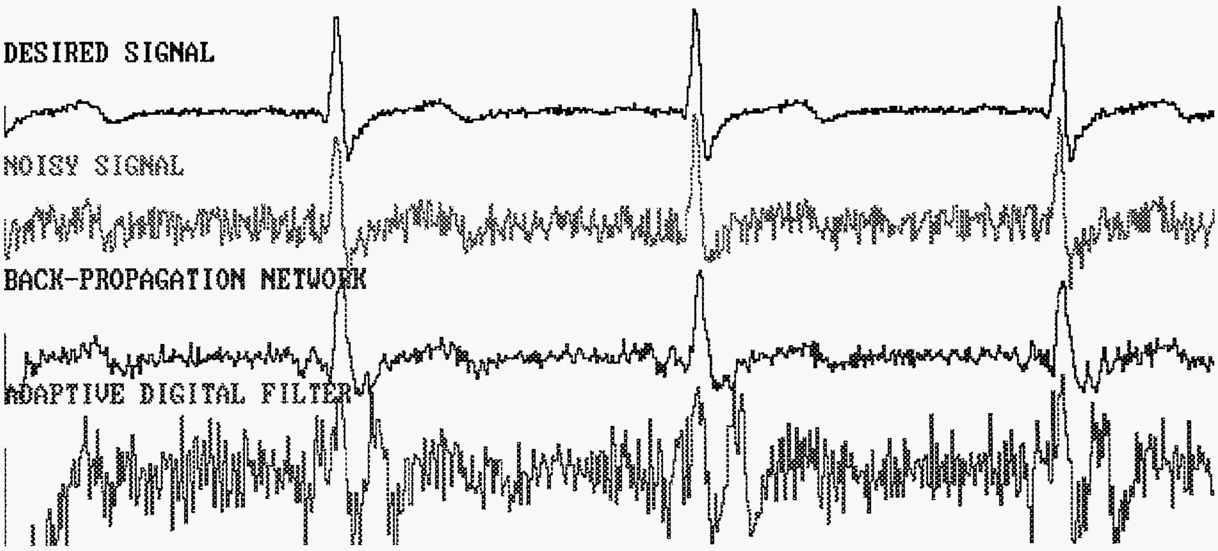

Figure 8
Training on given signal y_1(t) which is disturbed by noise component z(t). The lower signals show the performance of both network and filter after 5120 iterations.

It is obvious that the estimation y_1'(t) of y_1(t) is much better than y_1''(t). When training is continued (Figure 9) both the network and the filter get better in estimating the desired signal.

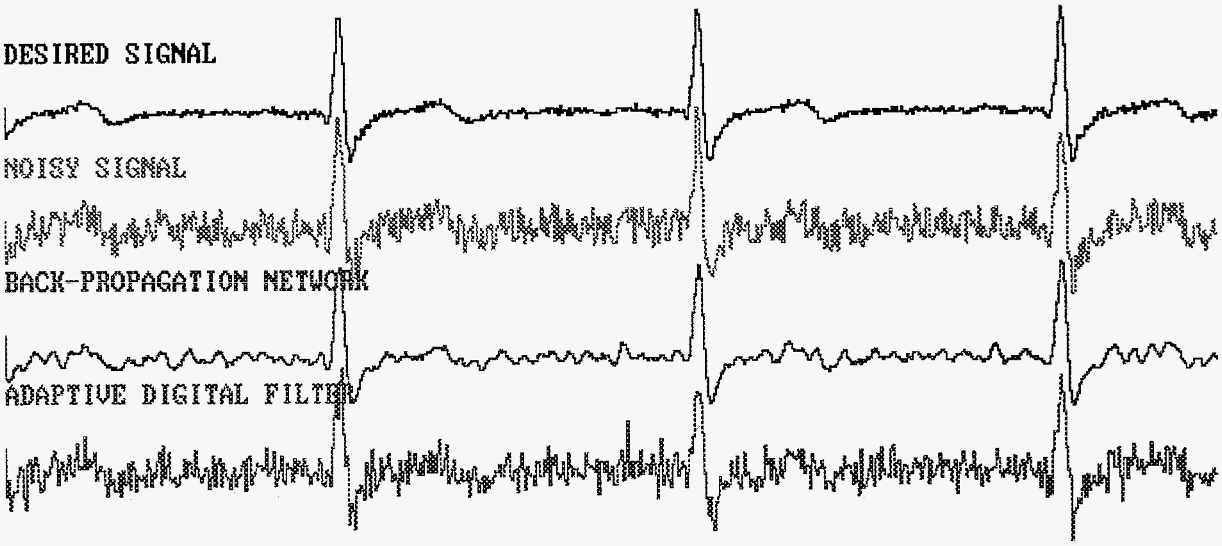

Figure 9
Performance of backpropagation network and adaptive digital filter in estimating desired signal after 51200 iterations.

After 51200 training iterations the networks output is reasonably satisfying, but the error in the output of the filter is still of the same size as the noise component $z(t)$ in the noisy signal. Only after 512000 training trials (Figure 10) the adaptive filter performs as well as the backpropagation neural network.

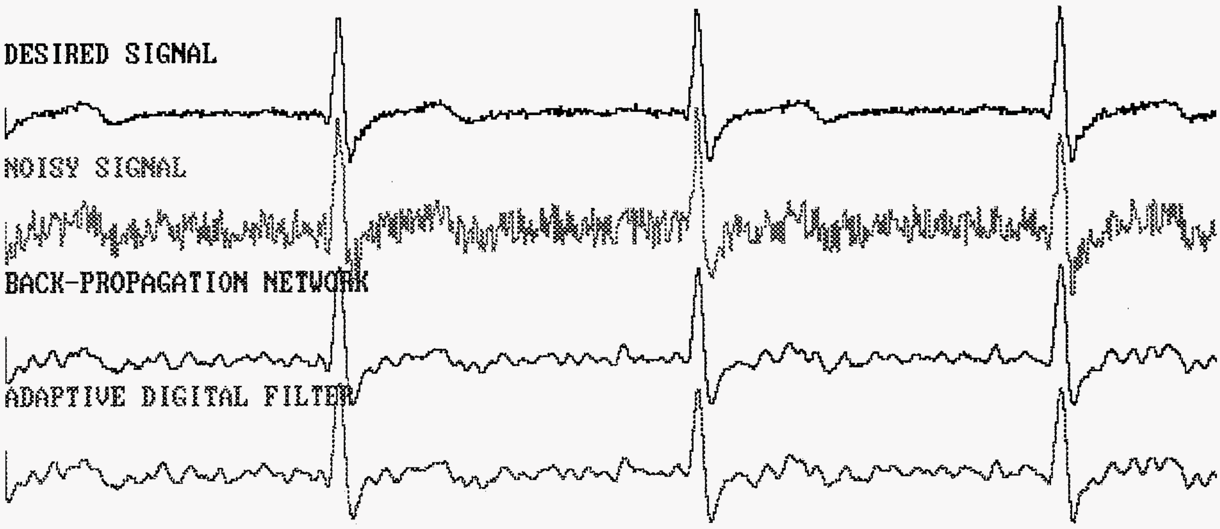

Figure 10
Equal performance after 512000 training iterations.

In this case training was switched off after 51200 iterations for time consumption reasons. After the weights are fixed, the two different noise reduction techniques are ready to be tested.

During operation both network and filter receive only the noisy signal as input. In Figure 11 this is $y_2(t) + z(t)$ and in Figure 12 it is $y_3(t) + z(t)$.

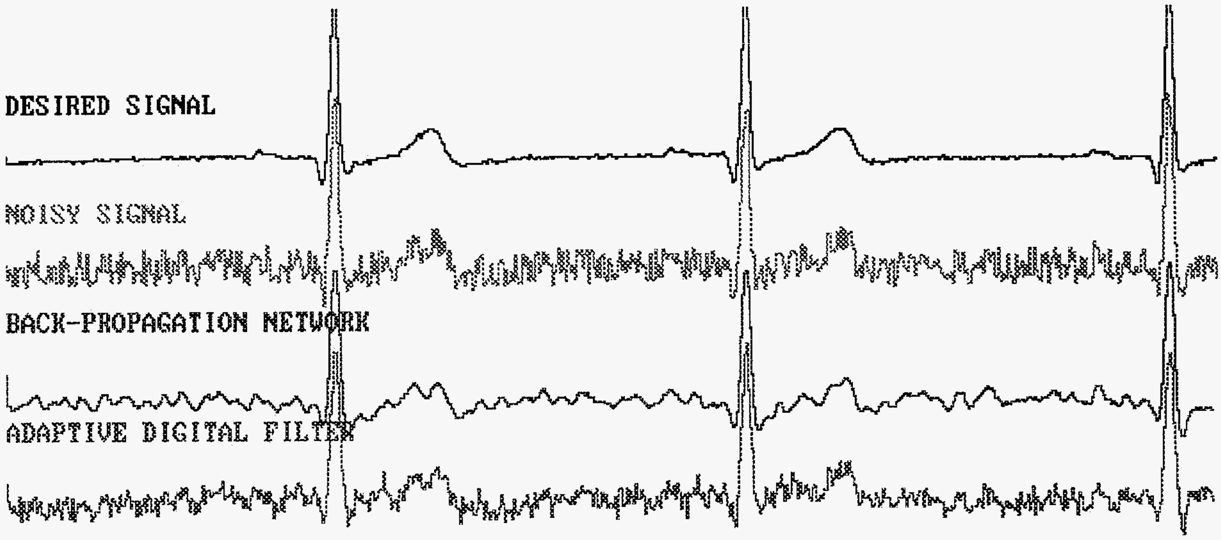

Figure 11
Testing on desired signal $y_2(t)$ when training is switched of after 51200 training trials.

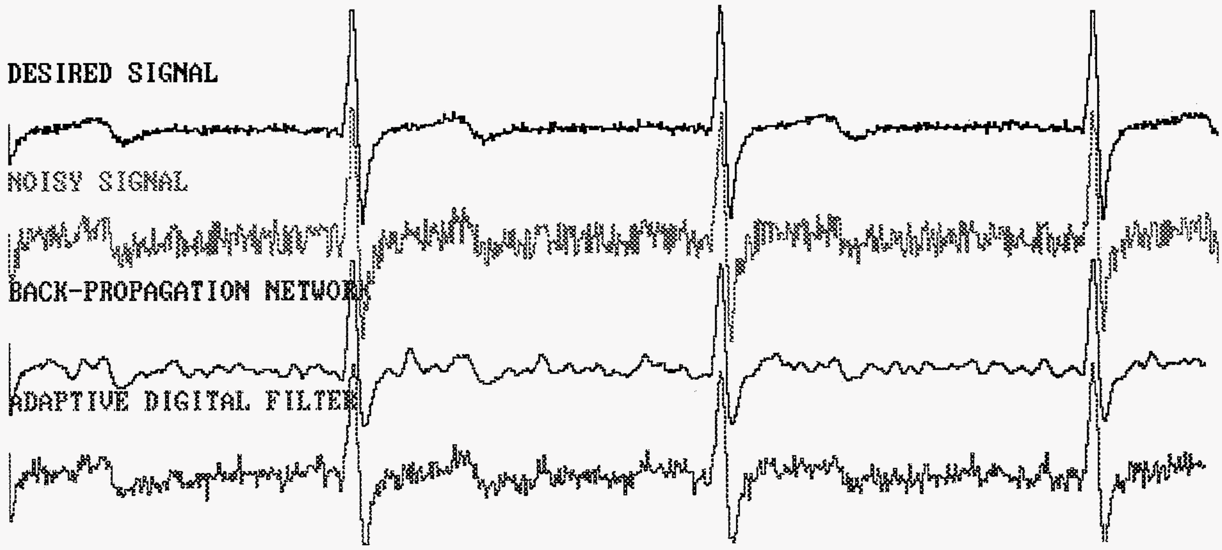

Figure 12
Testing on desired signal $y_3(t)$ when training is switched of after 51200 training trials.

From these Figures we can see that in fact only the network performs well in distracting noise from an unknown signal after it was trained with a similar (but not equal!) signal. The disturbance in the output of the filter is practically of the same size as $z(t)$. In Figure 10 we saw that the filter has to be trained 10 times longer than the network to perform just as good. The result of testing after 512000 training trials is shown in Figure 13.

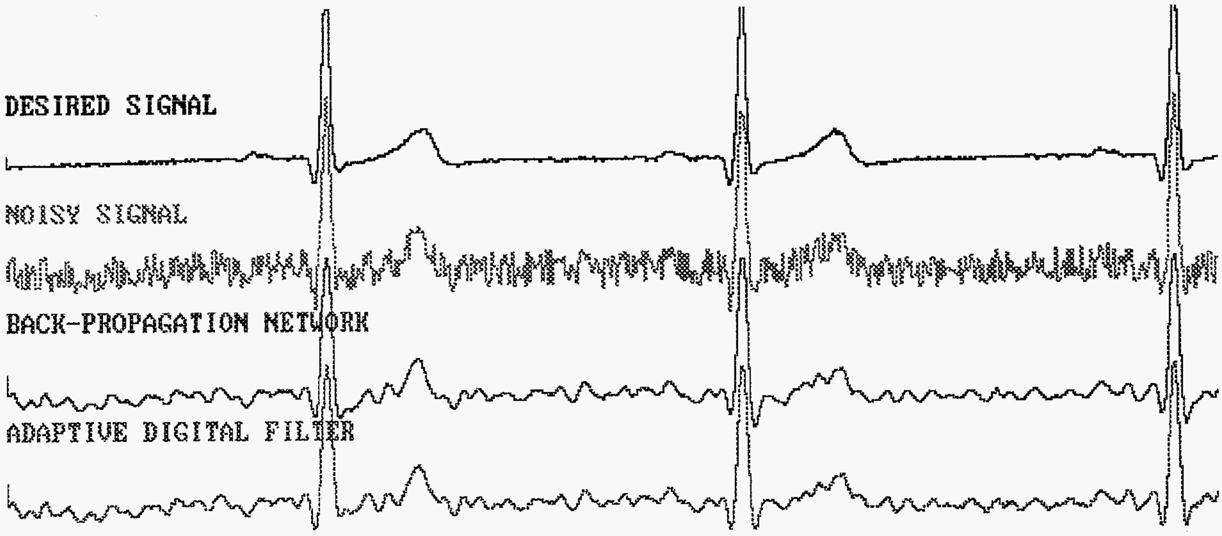

Figure 13
Testing on desired signal $y_2(t)$ when training is switched off after 512000 training trials; equal performance.

Conclusion.

Since the purpose of this example is just to illustrate the strength of the backpropagation neural network a qualitative judgement about both techniques is a little out of place here. The fact that the network is a very powerful tool in dealing with problems of the same kind is the most important conclusion that can be drawn here.

Chapter 3: Electrocardiography.

§ 3.1 Introduction.

One of the differences between the heart and skeletonmuscles is the fact that activation of the heart is conducted directly from fibre to fibre. Because of this direct impulse-conduction the activation of the heart takes place in a very homogeneous way. In fact we can speak from a electrical activationwave. Via leads applied to the skin of the body this signal can be registered and plotted against time. The resulting curve is called the electrocardiogram (ECG) and shows the changes of the electrical field caused by activation of the heart.

§ 3.2 History.

By the end of the eighteenth century human cardiac electrical activity was recorded for the first time (Figure 14). The design and application of a string galvanometer to record electrical activity of the heart by Willem Einthoven[6] was an important contribution to the development of electrocardiography. At present the electrocardiogram (ECG) is one of the most commonly used noninvasive investigation tools in the diagnostic armamentarium of the physician.

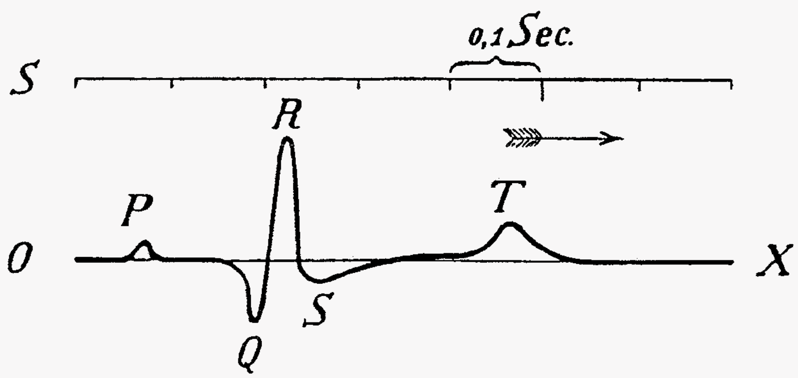

Figure 14
The early notation for the electrocardiogram as proposed by Einthoven. The largest deflection, positive or negative, was termed the R wave (Macfarlane and Lawrie eds., 1989: 8).

[6] Willem Einthoven, Dutch Physician and professor at University of Leiden, the Netherlands in the early-nineteenth century.

§ 3.3 The shape of the normal ECG.

§ 3.3.1 Introduction.

At any instant other than during the isoelectric period between ventricular repolarization and atrial depolarization, an electrical potential exists at every point of the body surface. This potential can be described as a vector with magnitude and direction.

The magnitude of this vector is inversely proportional to the cube of the distance between the moving electrical dipole and the electrode lead on the body surface. This is also one of the reasons why multiple leads, applied on different places of thorax and body, are used to record an electrocardiogram (Figure 15).

The electrocardiogram calculates the projection of the mean instantaneous vector on its lead axis by the electronic equivalent of vector addition. If the changing projections of this vector on a given lead axis are plotted against time, they produce the P, QRS and T waves in the electrocardiogram (Figure 16).

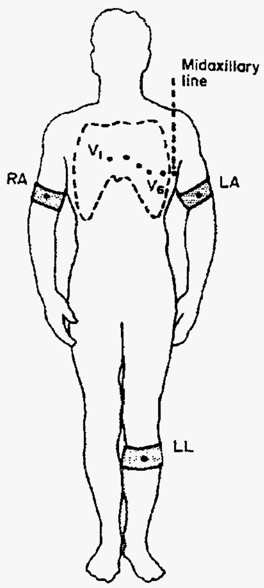

Figure 15
Lead placement. Electrodes attached to the limbs are used for the 'standard leads' I, II and III. Locations of leads V_1-V_6 as indicated (Macfarlane and Lawrie eds., 1989: 131).

§ 3.3.2 The P wave.

Atrial activation causes the P wave on the electrocardiogram. Although the P wave is the first wave in the electrocardiogram, the cardiac activation does not begin in the atria but in the sinus node which has no expression on the surface electrocardiogram. The normal P wave duration is about sixty milliseconds.

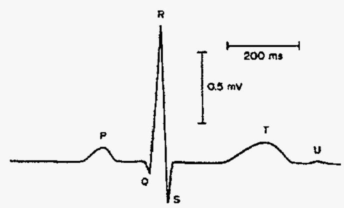

Figure 16
P-Q-R-S-T-U peaks on a lead II waveform (Macfarlane and Lawrie eds., 1989: 131)

§ 3.3.3 The QRS complex.

The QRS complex is caused by ventricular depolarisation and is usually the tallest and most rapid deflection on the electrocardiogram. The first negative deflection in the QRS complex, which is not seen in all leads, is called a Q wave. This Q wave is followed by a tall positive deflection, the R wave. The normal QRS complex ends with a second negative deflection, which is called the S wave. Normally the QRS complex takes about eighty milliseconds.

§ 3.3.4. The T wave.

Repolarization of ventricular myocardium generates the T wave. Generally it consists of a shallow upstroke, followed by a more rapid downstroke. In some leads a small U wave following the T wave may be visible. This U wave is thought to be due to ventricular Purkinje cell repolarization.

§ 3.4 Abnormalities in the ECG.

Malfunctions in the body have often an influence on the appearance of the ECG. Abnormalities in the shape of the ECG can sometimes provide such an important information for the diagnosis of a disease that the use of invasive methods to get information might not be necessary.

§ 3.4.1 Elevated Pressure and Hypertrophy.

Some cardiac defects can cause a big resistance in the bloodflow from the right chamber of the heart to the rest of the body. This means that the pressure in the right ventricle, which is normally around 20 - 30 mmHg., has to increase in order to keep the bloodflow constant. To be able to build up this elevated pressure, the right ventricular muscle mass has to grow unnaturally causing chamber enlargement or hypertrophy.

In the diagnosis of enlargement or hypertrophy of the cardiac chambers of especially children[7] the ECG can be very helpful. There are in fact several criteria that can appear in the ECG of a child. If a combination of these criteria occurs possible hypertrophy or eleveated pressure becomes more likely.

§ 3.4.2 Criteria.

The indications (Anderson et al., 1987: 274-276) for right ventricular hypertrophy:

→ The first criterion is the appearance of a QR pattern in the signal measured at

[7] The correlation between ECG and chamber size is much better in paediatric patients than in adults (Anderson et al., 1987: 272)

the right chest lead V_1 where a Q wave is unusual. This implies a right ventricular systolic pressure (*RVSP*) of 70 mmHg or more at any age.

→ The second criterion concerns changes in the T wave with increasing severety of hypertrophy (Figure 17) measured at V_1.

At the first sign of right ventricular hypertrophy The ECG shows a small R wave and a symmetrically inverted T wave (Figure 17A). With mildly increased pressure the T wave becomes iso-electric (flat) or upright (Figure 17B). When also the amplitude of the R wave increases (Figure 17C), the pressure height becomes severe. If finally the shape of the T wave is asymmetrically inverted, the pressure in the right ventricle becomes critical (Figure 17D).

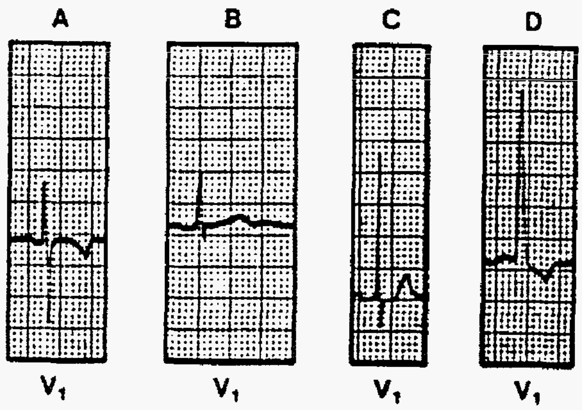

Figure 17
Progression of T wave changes in lead $V_1$with increasing (from A → D) severity of right ventricular systolic pressure (Anderson et al., 1987: 274).

→ The third criterion is the amplitude of the R wave in the ECG that is measured in lead V_1. Elevated pressure can cause hypertrophy.

Hypertrophy implies a bigger ventricular muscle mass which means that more electricity is needed for contraction. With right ventricular hypertrophy there is an increase in the voltage of the QRS complex in the leads that reflect the respective ventricle. Since the R wave in V_1 represents the depolarization of the right ventricle (*see* § 3.3.3), a relationship between its amplitude and the amount of right ventricular hypertrophy or the RVSP is quite likely.

In the past several formulas claiming a proportional relationship between the magnitude of R_{V_1} and the RVSP were devised. In the next chapter this matter will be explored further.

Generally right ventricular hypertrophy is suspected if the amplitude of R_{V_1} exceeds the 98th percentile for age (*see* Table I) and if R_{V_1} is 20 mmHg or more at any age, the right ventricular systolic pressure is equal to or more than systemic pressure.

→ The fourth criterion is the S wave amplitude of the ECG measured in lead V_6. If the amplitude of this wave exceeds the 98^{th} percentile for age (*see* Table 1), right ventricular hypertrophy is suspected.

→ The appearance of an abnormal high RS ratio (above 98% level; *see* Table I) in lead V_1, which correlates with right ventricular hypertrophy is the fifth criterion.

→ A sixth indication of right ventricular hypertrophy is a RSR' comlex in V_1. This means that if an "extra" R wave occurs after the first, it might be caused by right ventricular hypertrophy.

→ The final criterion is that of *right axis deviation*. Over the age of three months, right axis deviation correlates with right ventricular hypertrophy.

Table I

Summary of normal values, resulting from a statistical analysis with a number of subjects varying between n=100 and n=250 in every age-group (Anderson et al., 1987: 262 & 277).

Age-group	R wave in V_1 (mm)			S wave in V_6 (mm)			RS ratio in V_1		
	2%	mean	98%	2%	mean	98%	2%	mean	98%
Less than 1 day	5	14	26	0	3.2	9.6	0.1	2.2	U[8]
1-2 days	5	14	27	0	3.0	9.4	0.1	2.0	U
3-6 days	3	13	24	0	3.5	9.8	0.2	2.7	U
1-3 weeks	3	11	21	0	3.4	9.8	1	2.9	U
1-2 months	3	10	18	0	2.7	6.4	0.3	2.3	U
3-5 months	3	10	20	0	2.9	9.9	0.1	2.3	U
6-11 months	1.5	9.5	20	0	2.1	7.2	0.1	1.6	3.9
1-2 years	2.5	9	17	0	1.9	6.6	0.05	1.4	4.3
3-4 years	1	8	18	0	1.5	5.2	0.03	0.9	2.8
5-7 years	0.5	7	14	0	1.2	4.0	0.02	0.7	2.0
8-11 years	0	5.5	12	0	1.0	3.9	0	0.5	1.8
12-15 years	0	4	10	0	0.8	3.7	0	0.5	1.7

[8] U = undefined; the S wave may equal zero.

Chapter 4: RVSP[9] in relation to the R wave.

§ 4.1 Introduction.

The immediate cause of this chapter and the purpose of this report is the third criterion of § 3.4.2. It is obvious that we want to cure children suffering from right ventricular hypertrophy and the problems it brings along. This can be done by removing the resistance that causes the elevated pressure (which can rise up to around 200 mmHg.) operative. An additional problem that occurs here is that only up to a certain pressure in the heart an operation is possible. So far the pressure in the right ventricle can only be measured accurately with a quite invasive method; a catheter has to be brought into the right ventricle. Besides that the development of the pressure as time goes on has to be watched, which means that the measurement has to be repeated several times. Should we be able to "read" this pressure from the ECG, then we would have a very simple non-invasive method at our disposal to determine the pressure anytime we want.

As already mentioned, this subject has been examined before and different proportional relationships have been derived (Figure 18).

In 1958 Cayler et al. found:

$$RVSP = 3 \cdot R_{V_1} + 47 \tag{4.1}$$

Another relation was found twenty years later, in 1978 by Liebman and Plonsey:

$$RVSP = 5 \cdot R_{V_1} \tag{4.2}$$

(Formulas taken from Anderson et al., 1987: 275)

These formulas show that this matter has kept people busy and that, with great probability, there is a relationship between the amplitude of the electrical activation wave of the right ventricle (R wave) in lead V_1 and the systolic pressure (RVSP) in that same ventricle.

Nevertheless a simple proportional relation seems a little confined. The human body and the way our heart functions are so complex that direct proportionality sounds odd, at least until some uncertainties are cleared up.

[9]RVSP = Right Ventricular Systolic Pressure.

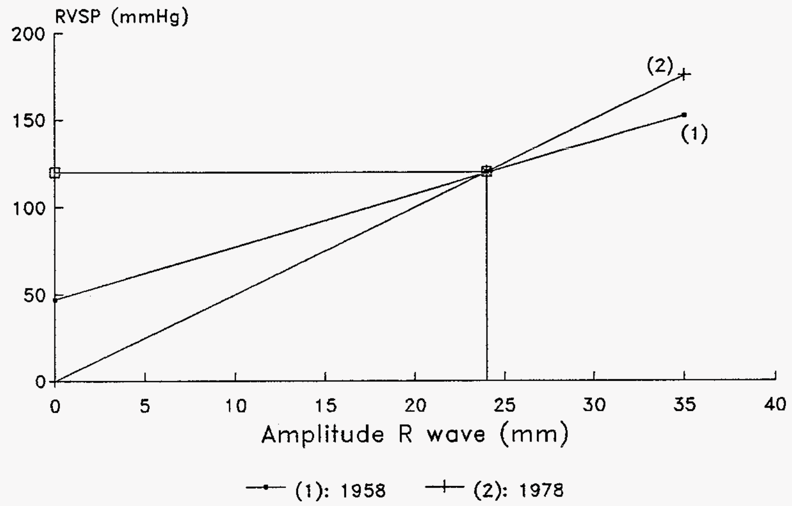

Figure 18
RVSP as a funtion of the amplitude of the R wave in lead V_1. The different relationships agree for f(R) = f(24) = 120.

Is it allowed to neglect a possible influence of factors as the volume of the ventricle, the thickness of the wall, the age of the person or the presence of a cardiac defect? Or even worse: What about unknown factors that should be taken into account? Because of its specific properties, a backpropagation neural network might be the right tool to try to find an answer to these questions.

If during training a neural network is fed with irrelevant data that does not correlate with the wanted (correct) output, it adapts itself by "cutting" the involved connections. This means that parameters of which the output is not a function will not affect the output, at least if training is carried out properly. When arbitrary factors are suspected to have an influence on a relationship between other variables, they should simply be fed to the network; they will be denied if there is no correlation.
In the case of elevated pressure and hypertrophy there should also be enough traing data available because currently the systolic pressure is still measured invasively next to the recording of the ECG.
These are some reasons to justify the attempt to try to find a reliable relationship between amplitude and pressure by using a backpropagation neural network.

§ 4.2 Experimental Setup.

For a start the aim was to write a computerprogram in C or Pascal that could simulate a backpropagation neural network with a desired architecture. This network should be trained using a set of approximately N = 350 ECGs together with corresponding RVSPs (measured invasively).

Next to the amplitude of the R wave in lead V_1, the following parameters were considered to be important beforehand, because a direct correlation with the RVSP was expected:

→ **The age of the child**; The amplitude of the R wave decreases as the age of a child increases. This can also be seen in Table I at page 23.

→ **The internal volume of the ventricle**; An increased volume has an increased enclosing surface. Compared to a standard volume the contracting power (that correlates with the R wave amplitude) has to be bigger in order to build up the same internal pressure (since $p = \frac{F}{A} \left[\frac{N}{m^2}\right]$).

→ **The thickness of the wall (which is the contracting muscle) of the ventricle**; With increasing hypertrophy (more muscle mass) a bigger impulse is needed for a contraction that builds up the same pressure as with normal wall thickness.

→ **T wave development**; The level of degeneration of the T wave is considered important out of intuition of the doctors involved in this project.

Given these parameters, a backpropagation neural network with six input units (R wave, age, volume, wall-thickness, T wave and bias input 1) and one output unit (RVSP) should be implemented.

Unfortunately at this point we ran into some organizational problems. Due to these problems it was not possible to set up this project in the desired way. Some severe restrictions had to be accepted.

The set of training data available consisted of only 96 cases of children suffering from 3 different cardiac defects (Figure 19). In Appendix B an overview of the data can be found. All data, but age and pressure, was retrieved from the electrocardiogram. The important parameters are: Age, RVSP, R in V_1 and T in V_1.
The RVSP in Appendix B that corresponds with every single set of data was measured invasively using a catheter at the same time the ECG was recorded. The value of this pressure is needed as a reference (the so-called "correct output") to train the network. In Figure 20 this value is plotted against the respective values of the R wave

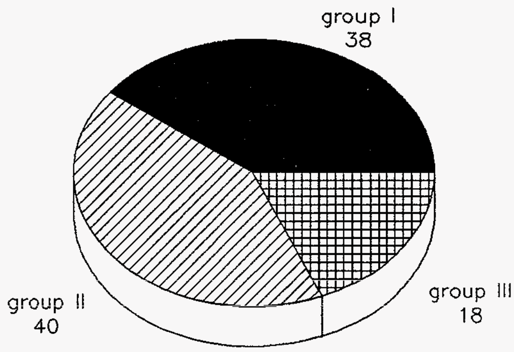

Figure 19
Total set of training data.
Group I: Ventricular Septal Defect.
Group II: Tetralogy of Fallot.
Group III: Pulmonary Artery Stenosis.

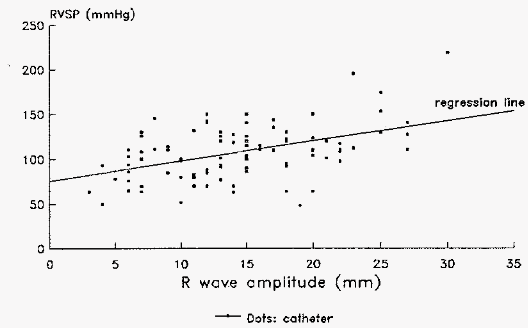

Figure 20
The RVSP that was measured invasively plotted against the R wave amplitude in V_1.

Next to the shortage of data it was not possible to determine both the internal volume and the wall thickness of the right ventricle accurately. These two parameters had to be neglected.
Since time was also running short, the development of a computerprogram in C or Pascal was considered to be too time consuming. To be able to do at least some testing, a short program in Basic was written. The resulting computerprogram can be found in Appendix A.

This program simulates a simple backpropagation neural network with five input units and one output unit. Initial weights are arbitrary and all training data is normalised to 1 before it is used for calculations.

The following parameters can be fed to the network:

→ **R wave**; the value of the amplitude in lead V_1 in mm.
The values are normalised to 1 by dividing by 30 (the highest overall value).

→ **T wave**; the shape is divided in 6 classes, corresponding with increasing severity of hypertrophy and elevated pressure (*see also* § 3.4.2 *and* Appendix B). The different shape-classes are:
a: upright T wave (input value = 1).
b: flat T wave (input value = 2).
c: bi-phasic T wave (input value = 3).
d: inverted T wave (input value = 4).
e: asymmetrically inverted T wave with an amplitude ≤ 2 mm. (input value = 5).
f: asymmetrically inverted T wave with an amplitude > 2 mm. (input value = 6).
The values are normalised to 1 by dividing by 6.

→ **Age**; The age of the children is divided in the following 5 classes:
a: 0 - 0,3 years (input value = 1).
b: 0,3 - 0,5 years (input value = 2).
c: 0,5 - 1 years (input value = 3).
d: 1 - 3 years (input value = 4).
e: 3 - ... years (input value = 5).
The values are normalised to 1 by dividing by 5.

→ **Wall thickness**; Not taken into account because no accurate values were available. So in fact only four input units were used.

→ **Bias input**; input value = constant = 1.

During training the network is also provided with the corresponding value of the right ventricular pressure in mmHg. This value is normalised to 1 by dividing by 219 (the highest overall value). The network needs this pressure to compare it with its own estimation and to determine the error it made.

The output of the program is its estimation of the RVSP according to the ECG as if the RVSP was not known. The output of the network is compared to the correct output every training iteration and the weights are changed according to the difference between the two values.

Training the network takes place in iterations as follows:

```
R-WAVE=? 8
T-WAVE=? 1
AGE=? 1
PRESSURE=? 111
CALCULATED PRESSURE IS 59.56148
OUTPUT NETWORK ERROR IS ER= .2348791
```

In this case all input was fed to the program manually. After all data is used, the weights are fixed and the network should then be ready for testing.

§ 4.3 Results.

After all available data was divided into classes, the program was executed and the network was trained during 96 training trials. After that the weights were fixed and the network was no longer provided with the "correct" RVSP.

Unfortunately we had no extra testing data at our disposal. All data available had to be used for training the network. To make it possible to do at least some testing, the training data was used again, but now without corresponding RVSP, to test the network. The program was only provided with the R wave, the T wave and the age, while the error feedback (*see* Appendix A, lines 165-194: "Backward Pass") was switched off. The resulting output of the network together with the other theoretical relationships is shown in Figure 21.

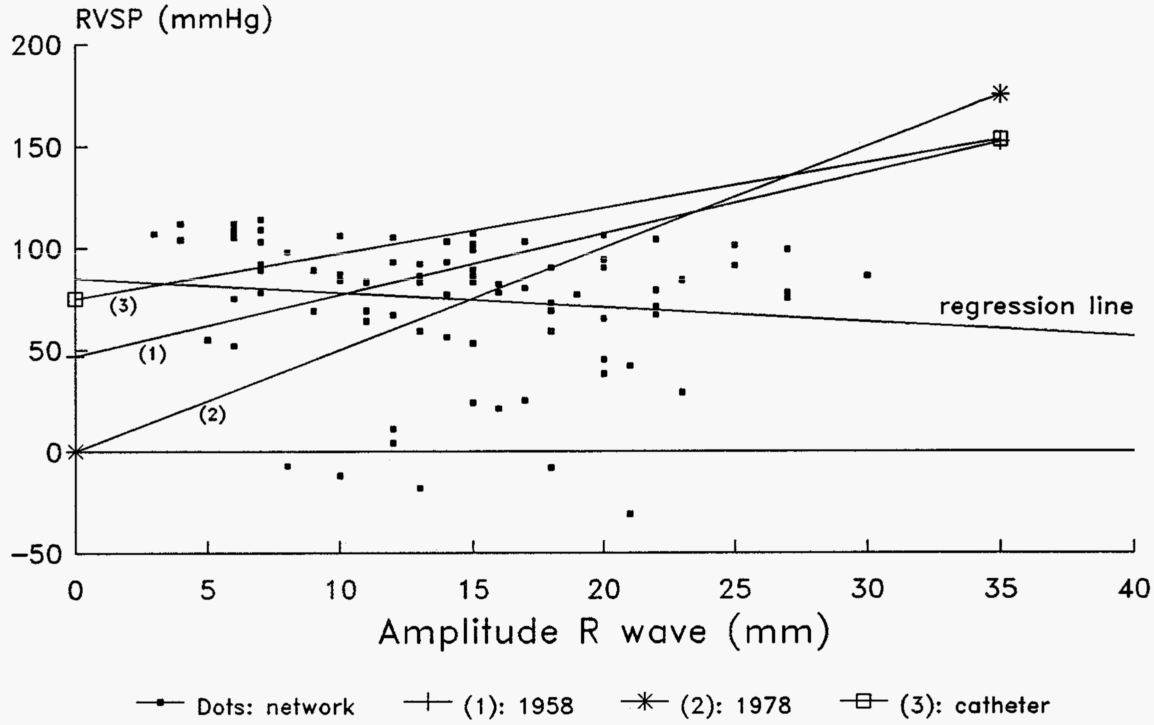

Figure 21
The RVSP as calculated by the backpropagation neural network plotted against the amplitude of the R wave in lead V_1.

§ 4.4 Discussion.

Obviously the neural network is not able to predict the value of the RVSP as a function of the R wave accurately in this situation. Even though it is not entirely correct to use the training data also for testing the network, this data should be "known" to the network and so it should do better in estimating the correct output. From Figure 21 it can be seen that the regression line of the output predicts a declining relationship which is very strange because all relationships that were devised so far were increasing proportional. Next to this even impossible negative values are found.

Although there seems to be no correlation at all, various reasons and problems around the set up of the experiment that might cause this malfunctioning can be appointed.

First of all a set of training data consisting of only 96 cases can hardly be called sufficient from a statistical point of view. Especially in this case because they might be other yet unexplored noise sources.

Second some parameters which were expected to have an influence on the relationship had to be neglected because they could not be measured accurately (*see* § 4.2). Now there is no way of telling whether or not the volume and wall-thickness of the right ventricle have affected the network's output.

Some doubts about the accuracy concerning values of the R wave and especially the RVSP in Appendix B that are used as input are also justified. The error in the amplitude of the R wave can vary between 2 and about 5 mm. this was not taken into account. Looking at Figure 22, the values of the invasively measured RVSP seem to agree quite good with the relationships from § 4.1, but the variation is very big and one might wonder if fitting these values makes any sense.

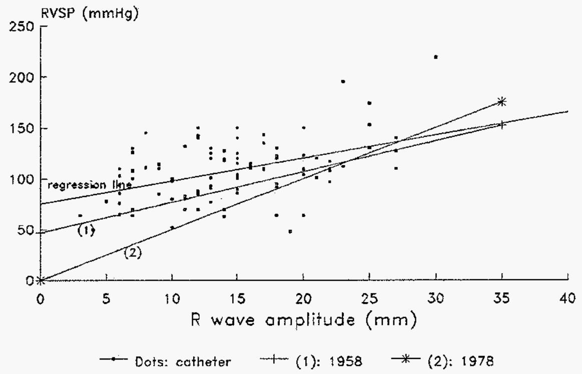

Figure 22
The values of the invasively measured RVSP plotted against the R wave; (1) and (2): earlier devised relationships.

But also the accuracy of the measurement of the single RVSP can be questioned. In Appendix B at page 40, with training set nr. 9 it can be seen that two measurements were made at the same time; A difference of 17 mmHg. occurred. At page 41 and 42, the training set 16 and 5 are printed twice because a later measurement was also available. In both situations the value of the latter RVSP is smaller then the first. It is commonly known that as time goes on and hypertrophy increases, the pressure should also increase.

Another problem is that only the ECGs of defected hearts were used, because there is no reason to perform an invasive measurement on a healthy heart. So no standard cases were available for comparison.

Finally there might be other unknown influences that should be taken into account. This also concerns the regression lines in the Figures 20, 21 and 22. It is not certain that the wanted relationship is proportional, but linear regression was the only method that made it possible to compare the results.

§ 4.5 Conclusions.

It might seem odd that this project was continued when a lot of the problems were known beforehand. Unfortunately it is true that no qualitative conclusions can be drawn because it was not yet possible to prove and determine a relationship between the amplitude of the R wave of the electrocardiogram in lead V_1 and the right ventricular systolic pressure. But this report partly describes just the start of a project which will probably be continued. Hopefully the report can serve as a basis for a more extensive and successful experimental setup with which the wanted relationship can be profoundly proved and defined so that invasive measurements might become superfluous in the future.

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Glossary.

Arteria Pulmonalis Diastolic Pressure: The pressure in the arteria pulmonalis at the end of the relaxation-phase of the right ventricle

ECG: Electrocardiogram.

Generalized delta rule learning law: Learning law that reduces the error by moving the weightvector in the direction of the gradient of the error until a minimum is reached (*see* **Learning law**).

Hidden layer: Layer of a neural network that is not directly connected to the periphery. All layers except input/output layers are hidden.

Learning law: Equation according to which weights are adapted during transformations when a neural network is trained.

Learning rate: factor that sets the learning speed of a neural network by determining the step changing the weights every training iteration.

Neural network: Information processing system that autonomously develops operational capabilities in adaptive response to an information environment.

Neurocomputing: Technological discipline concerned with information processing based on transformations instead of algorithms or strictly specified rules.

Perceptron: First important neural network structure consisting out of one or more processing elements.

Processing element: A single unit in a neural network.

Programmed computing: Traditional way of information processing using computers. Problems are solved with the help of computerprograms that are written according to algorithms.

Prototype network: Network that creates a set of specific input/output examples. Unknown functions are compared with these figures and that provides an estimation of the wanted function (≠ feature network).

Right Axis Deviation: Diagnosis criterion calculated out of values of deflections in the electrocardiogram in different leads.

RVH: Right ventricular hypertrophy. Unnatural growth of the muscle that surrounds the ventricle.

RVSP: Right ventricular systolic pressure. The highest pressure that occurs during the contraction of the right ventricle

Weights: Transformation multiplication factors.

Vita.

At present (summer 1991) Maarten Hut is a 23 years old graduate student at the Eindhoven University of Technology, The Netherlands. In 1987 he started to study Physical Engineering and switched to Mechanical Engineering in 1988. As a graduate he is now specializing in Biomedical Engineering and if all goes well he will finish his studies in about two years from now. This project at Belgrade University, Yugoslavia represents his first practical training period.

Appendix A: Computerprogram.

This section contains the computerprogram written in Basic as it was used to simulate the backpropagation neural network. The program implements a network with $n = 5$ input units (of which one serves as refence with a constant input value of 1, the so-called bias input), $2n+1 = 11$ *hidden layer* units and 1 output unit.

```
15   DIM W(5,11): DIM V(11): DIM Q(11): DIM IN(6):DIM F(11):DIM
     L(11):DIM C(5,11):DIM G(5,11):DIM X(5,11)
20   DIM P(11): DIM DEL(11): DIM DELV(11): DIM DLV(11): DIM
     DLW(5,11): DIM DELW(5,11)
25   A=0: B=0: ALPHA=0.8:ETA=0.5:IN(1)=1:IN(5)=0.5


29   FOR I=1 TO 5
30   FOR J=1 TO 11
31   W(I,J)=RND-0.5
32   REM INPUT "W(I,J)=";W(I,J)
34   V(J)=RND-0.5
36   NEXT J
40   NEXT I
42   FOR J=1 TO 11
44   DLV(J)=RND-0.5
46   NEXT J


56   INPUT "IF YOU WANT TO GET WEIGHTS ON THE SCREEN - PRESS
     1";Z: IF Z=1 THEN GOSUB 250


60   B$=INKEY$: IF B$="S" THEN GOTO 500
62   REM INPUT "INPUT DATA AS FOLLOWS:1";IN(1)
64   INPUT "R-WAVE=";INABS(2)
66   INPUT "T-WAVE=";INABS(3)
68   INPUT "AGE=";INABS(4)
70   REM INPUT "WALL THICKNESS=";IN(5)
72   INPUT "PRESSURE=";INABS(6)
74   IN(2)=INABS(2)/30
76   IN(3)=INABS(3)/6
78   IN(4)=INABS(4)/5
80   IN(6)=INABS(6)/219


146 REM "FORWARD PASS - BLOCK"
148 Z=O:OPUT1=0
150 FOR J=1 TO 11
152 FOR I=1 TO 5
154 Q(J)=Z+W(I,J)*IN(I): Z=Q(J)
155 NEXT I
156 REM PRINT "J=";J
```

```
157 REM PRINT "Q(J)=";Q(J)
158 F(J)=1/(1+EXP(-Q(J))):P(J)=F(J)*V(J):OPUT1=OPUT1+P(J):OPUT
    =OPUT1
159 REM PRINT "F(J)=";F(J)
160 NEXT J


165 REM "BACKWARD PASS - BLOCK"
170 ER=IN(6)-OPUT
190 FOR J=1 TO 11
192 DEL(J)=F(J)*(1-F(J))*V(J)*ER:DEL(J)=ALPHA*DLV(J)+ETA*F(J)*
    ER: V(J)=V(J)+DEL(J):DLV(J)=DELV(J)
194 NEXT J


200 FOR J=1 TO 11
205 FOR I=1 TO 5
210 DELW(I,J)=ALPHA*DLW(I,J)+ETA*IN(I)*DEL(J):W(I,J)=W(I,J)+DE
    LW(I,J): DLW(I,J)=DELW(I,J)
215 NEXT I
220 NEXT J


224 NORM=OPUT*219
225 PRINT "CALCULATED PRESSURE IS ";NORM
228 PRINT "OUTPUT NETWORK ERROR IS ER=";ER

230 GOTO 56


250 CLS:FOR I=1 TO 5
252 B=16*I-14
254 LOCATE 1,40
255 FOR J=1 TO 11
256 LOCATE J,B
258 F$="###.##":PRINT USING F$;W(I,J)
270 NEXT J
272 NEXT I
274 FOR J=1 TO 11
276 L(J)=INT(V(J))
278 A$="###.##":PRINT USING A$;V(J)
280 NEXT J



290 RETURN



500 END
```

Appendix B: Experimental Data.

Group I (Ventricular septal defect with pulmonary hypertension)

nr	Age (yrs)	RVSP[10] ± 5 (mmHg)		Cal. fact * 1/10	Right Axis Deviation ± 1 (mm)					Q in V_1 present/ absent	R in V_1 Ampl. ± 2 (mm)	R/S ratio in V_1 ± 1 (mm)	T in V_1 shape[11]; amplitude ± 1 (mm)	R/S ratio[12] in V_6		
			APDP[13]		R^I	S^I	R^{aVF}	S^{aVF}	Ax.					R	S	R/S
11	0.2	111/0	105/40	1.1	9	8	3	1	63	absent	8	4	a; 2	17	6	2.8
1	0.3	94/0	x	1	10	6	7	5	27	absent	6	2	b	x	x	x
2	0.4	122/0	115/26	1.1	5	9	10	1	114	present	18	x (no S)	d; 3	x	x	x
3	0.4	78/0	72/16	1.1	10	7	10	3	67	absent	5	x (no S)	?	x	x	x
29	0.3	115/0	110/35	1.1	10	15	12	2	117	present	16	x (no S)	?	19	23	0.8
31	0.5	114/0	100/30	1.1	9	5	0	17	103	absent	9	x (no S)	e; 2	10	11	0.9
33	0.3	85/0	85/35	1.2	7	6	17	3	86	absent	12	x (no S)	a; 1	17	20	0.9
36	0.5	70/0	85/23	1	13	8	11[14]	7[14]	50	absent	12	2	d; 3	x	x	x
37	0.4	108/0	100/35	1	5	5	11	4	90	absent	22	x (no S)	e; 2	x	x	x
4	0.9	115/0	67/12	1.1	11	8	3	6	135	absent	15	2	d; 3	x	x	x
5	0.6	93/0	88/28	1.1	9	7	7	0	74	absent	4	x (no S)	f; 3	10	4	2.5
7	1	48/0	42/15	1	8	10	18	2	97	absent	19	x (no S)	d; 2	9	9	1
10	0.8	63/0	50/3	1.2	13	0	19	2	53	absent	14	1	?	28	6	4.7
16	1	110/0	98/30	1.2	10	6	17[15]	14[15]	26	absent	17	x (no S)	d; 3	19	6	3.2
17	0.9	110/0	110/57	1.1	12	3	11	14	-20	absent	16	1	d; 2	23	10	2.3
19	0.8	135/0	92/25	1.1	8	8	5	7	-90	absent	17	x (no S)	d; 2	x	x	x
22	0.7	125/0	103/40	1.1	13	15	23	0	95	present	15	x (no S)	?	20	28	0.7
28	0.8	110/0	110/9	1.2	16	19	16	6	107	absent	9	1	?	4	4	1
30	0.8	119/0	119/38	1.1	7	10	18	0	99	present	14	2	e; 2	14	18	0.8
34	0.8	110/0	110/50	1.1	9	11	29	4	96	absent	27	3	e; 1	16	6	2.7
35	0.8	76/0	43/0	1.1	11	5	3	10	131	absent	6	x (no S)	b	14	8	1.8
40	1	83/0	75/38	1.1	10	10	17	4	90	absent	11	x (no S)	b	20	25	0.8
41	0.8	77/0	70/7	1.1	4	6	10	1	103	absent	13	x (no S)	b	2	3	0.7
42	0.8	110/0	110/57	1.1	13	5	6	12	143	absent	20	1	b	23	12	1.9

[10] Right Ventricular Systolic Pressure.

[11] Shape normalised in 6 classes:
- **a**: upright
- **b**: flat
- **c**: bi-phasic
- **d**: inverted
- **e**: inverted & assymmetrical; ampl ≤ 2 (mm)
- **f**: inverted & assymmetrical; ampl > 2 (mm)

[12] Uncalibrated Values.

[13] *Arteria Pulmonalis Diastolic Pressure.*

[14] Lead III values used instead of *aVF*

[15] Lead II values used instead of *aVF*

nr	Age (yrs)	RVSP ± 5 (mmHg)		Cal. fact * 1/10	Right Axis Deviation ± 1 (mm)					Q in V_1 present/ absent	R in V_1 Ampl. ± 2 (mm)	R/S ratio in V_1 ± 1 (mm)	T in V_1 shape; amplitude ± 1 (mm)	R/S ratio in V_6		
			APDP		R^I	S^I	R^{aVF}	S^{aVF}	Ax.					R	S	R/S
8	3	104/0	100/30	1	4	11	7	0	135	absent	20	2	?	8	5	1.6
14	1.5	90/0	80/20	1	6	8	16	10	108	absent	15	x (no S)	5; 2	15	10	1.5
15	1.1	118/0	x	1.1	4	10	13	1	117	present	14	x (no S)	2	9	3	3
18	1.1	95/0	87/24	1.1	8	4	9	0	66	absent	18	6	4; 1	x	x	x
24	1.5	100/0	95/37	1.1	9	5	3	11	-63	present	7	4	1; 2	10	24	0.4
27	1.8	80/0	59/15	1	3	5	14	0	98	absent	11	x (no S)	2	x	x	x
32	2	64/0	58/22	1.2	10	1	3	10	-52	absent	3	0.3	4; 3	9	x	x
9	4	130/0[16]	130/72	1.1	10	16	5	2	153	absent	25	x (no S)	6; 3	19	20	1
21	4.5	70/0	70/18	1.1	2	4	11	4	106	absent	7	2	6; 3	15	6	2.5
23	15	127/0	127/50	1.1	1	10	6	9	198	absent	27	x (no S)	6; 5	11	11	1
25	6	127/0	117/60	1.1	5	2	12	10	37	absent	14	x (no S)	4; 2	22	8	2.8
26	8	110/0	69/26	1.1	4	7	1	6	-121	absent	22	x (no S)	6; 3	15	10	1.5
38	11	125/0	125/52	1	7	11	7	0	120	absent	13	3	1; 3	19	12	1.6
39	6	109/0	109/22	1.1	10	13	9	6	135	absent	20	x (no S)	3	x	x	x

Group II (Tetralogy of Fallot)

nr	Age (yrs)	RVSP ± 5 (mmHg)	Cal. fact * 1/10	Right Axis Deviation ± 1 (mm)					Q in V_1 present/ absent	R in V_1 Ampl. ± 2 (mm)	R/S ratio in V_1 ± 1 (mm)	T in V_1 shape; amplitude ± 1 (mm)	R/S ratio in V_6		
				R^I	S^I	R^{aVF}	S^{aVF}	Ax.					R	S	R/S
1	1.0	109/0	1	3	9	13	x	114	absent	17	3	1; 2	x	x	x
3	0.3	120/0	1.2	7	9	7[15]	6[15]	123	absent	13	x (no S)	1; ?	x	x	x
5	0.3	91/0	1.2	x	x	x	x	x	absent	13	2	1; 2	5	7	0.7
7	0.3	140/0	1.2	4	9	9	2	125	absent	12	x (no S)	2	x	x	x
4	1	112/0	1.1	4	10	5[15]	7[15]	161	absent	23	5	2	14	16	0.9
6	0.3	98/0	1	6	8	12	2	101	absent	10	5	1; 2	6	6	1
8	0.9	85/0	1.1	9[14]	x[14]	4	x	106	absent	9	2	2	8	x	x
9	0.6	117/0	1.1	10	9	14	6	83	absent	22	x (no S)	4; 3	25	18	1.4
10	0.4	100/0	1.1	3	10	11	3	131	absent	15	3	2	3	15	0.2
11	0.3	101/0	1.2	6	12	9[17]	6[17]	-172	absent	21	6	1; 3	15	10	1.5
12	0.9	101/0	1.2	1	5	6	2	135	absent	13	x (no S)	4; 3	3	15	0.2
13	0.3	64/0	1.2	7	8	1	x	135	absent	18	x (no S)	2	8	12	0.7
2	0.5	113/0	1.1	9	17	10	6	153	present	16	x (no S)	6; 3	5	20	0.3
1	3	104/0	1	5	7	10	x	101	present	15	x (no S)	5; 2	7	3	2.3

[16] Another measurement was made at the same time; RVSP = 147/0 was found!

[17] *aVR* values used instead of *aVF*.

nr	*Age (yrs)*	*RVSP ± 5 (mmHg)*	Cal. fact * *1/10*	Right Axis Deviation ± 1 (mm)					Q *in* V_1 *present/ absent*	*R in* V_1 *Ampl. ± 2 (mm)*	*R/S ratio* in V_1 ± *1 (mm)*	*T in* V_1 *shape; amplitude ± 1 (mm)*	*R/S ratio* in V_6		
				R^I	S^I	R^{aVF}	S^{aVF}	Ax.					R	S	*R/S*
2	3	64/0	1.1	6	10	10	x	124	absent	7	4	?	9	6	1.5
3	1.7	140/0	1.1	9	18	5	x	151	present	27	x (no S)	4; 7	x	x	x
4	2.5	150/0	1.1	4	9	11	x	114	absent	12	4	1; 2	x	x	x
5	5	130/0	1.1	3	12	9	x	135	absent	18	x (no S)	1; ?	5	9	0.6
6	3	92/0	1.1	4	12	2	5	160	absent	18	6	4; 4	3	10	0.3
7	1.8	86/0	1.1	8	9	12	x	95	present	15	x (no S)	5; 2	10	2	5
8	4	108/0	1.2	3	2	3	7	104	absent	7	1	1; 3	6	14	0.5
9	14	145/0	1	6	12	17	3	114	absent	8	x (no S)	5; ?	13	18	0.7
10	1.7	132/0	1.1	6	6	13	x	90	absent	11	3	1; 1	6	3	2
11	3	143/0	1.1	3	14	14	2	133	absent	17	x (no S)	5; 4	8	10	0.8
12	1.3	150/0	1.1	2	26	19	2	145	present	15	5	3	10	4	2.5
13	3	150	1.1	4	20	16	x	135	absent	20	3	1; 4	9	8	1.1
14	4	97/0	1	3	7	7	1	124	absent	22	4	?	x	x	x
15	7	110/0	1.1	x	5	12	x	113	absent	6	1	4	4	5	0.8
16	4	130/0[18]	1.1	12	16	12	x	108	absent	7	x (no S)	6; 5	2	2	1
16	5.5	123/0[9]	1.1	7	14	9	2	135	absent	20	x (no S)	6; 4	6	6	1
17	10	142/0	1	4	24	14	2	149	present	12	x (no S)	2	3	15	0.3
18	5	130/0	1	2	8	7	x	131	absent	7	2	6; 3	16	18	0.9
19	12	140/0	1.1	2	9	7	x	135	absent	15	3	6; 5	3	15	0.2
20	2	120/0	1.1	4	12	6	3	159	absent	21	10	1; 2	11	11	1
21	1.3	64/0	1.1	5	7	10	3	106	absent	20	x (no S)	5; 2	15	4	3.8
22	2	110/0	1.1	15[15]	5[15]	9	x		present	20	x (no S)	6; 4	20	18	1.1
23	2.5	120/0	1	7	10	18	x	99	absent	18	3	2	8	10	0.8
24	19	120/0	1.1	10	5	4[17]	7[17]	149	absent	15	3	4; 3	18	13	1.4
25	12	174/0	1.1	6	10	15	x	105	absent	25	x (no S)	4; 4	18	13	1.4
26	2.5	100/0	1	10	3	5	x	35	present	10	x (no S)	2	4	9	0.4
27	3.5	93/0	1.1	2	8	4	x	146	absent	13	3	1; 1	1	5	0.2
28	8.5	103/0	1.1	5	6	14	3	95	absent	15	3	?	21	20	1

[18] Both at the age of 4 and 5,5 years pressure was measured. A year and a half after the first measurement a decrease of 7 mmHg was found!

Group III (Pulmonary Artery Stenosis)

nr	*Age (yrs)*	*RVSP ± 5 (mmHg)*	Cal. fact * *1/10*	Right Axis Deviation ± 1 (mm)					Q *in* V_1 *present/ absent*	*R in* V_1 *Ampl. ± 2 (mm)*	*R/S ratio* in V_1 *± 1(mm)*	*T in* V_1 *shape; amplitude ± 1 (mm)*	*R/S ratio* in V_6		
				R^I	S^I	R^{aVF}	S^{aVF}	Ax.					R	S	*R/S*
2	6	65/0	1.1	2	5	6	2	127	absent	6	6	5; 3	7	5	1.4
3	4	100/0	1.1	3	6	15	4	105	absent	10	5	4; 3	12	8	1.5
3	7	130/0	1.2	5	9	14	4	112	absent	13	x (no S)	2	15	6	2.5
5	11[19]	86/0	1.1	5	1	11	x	70	absent	6	3	5; 1	7	3	2.3
5	12[19]	52/0	1.2	8	3	13	x	69	absent	10	4	1; 1	18	2	9
6	2	70/0	0.9	6	9	5	x	121	absent	14	x (no S)	2	3	x	x
7	3	126/0	1	1	7	14	2	117	absent	7	x (no S)	4; 2	x	x	x
8	4	153/0	1	4	13	15	4	129	absent	25	5	4; 3	6	12	0.5
9	4.5	103/0	1.1	5	3	3	4	153	absent	6	1	4; 2	5	3	1.7
10	6	80/0	1.1	1	6	15	2	111	absent	10	5	4; 3	25	6	4.2
11	9	219/0	1.1	8	19	4[15]	15[15]	-145	present	30	x (no S)	4; 8	x	x	x
12	12	88/0	1.1	3	7	10	3	120	absent	12	3	4; 2	11	15	0.7
13	3	70/0	1	3	10	10[14]	3[14]	152	absent	11	x (no S)	2	7	8	0.9
14	7.5	50/0	1	4	5	10	2	97	absent	4	x (no S)	5; 1	12	7	1.7
15	2	195/0	1.1	5	4	1	5	104	present	23	x (no S)	4; 5	6	10	0.6

[19] Both at 11 and 12 years pressure was measured. A year after the first measurement a decrease of 34 mmHg. was found!