AUSCULTATORY BLOOD PRESSURE MEASUREMENT USING HMMS

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ABSTRACT

This paper reports on a study of applying an HMM-based labeler along with a taylored feature extraction to Korotkoff sounds. These sounds can be heard through a stethoscope during the auscultatory blood pressure measurement usually done at medical practices. While this method works well when the patient is at rest, interfering noise from muscles and joints cause major problems when the subject is doing any activities like sports or fitness exercises. We propose a signal processing and classification method to overcome these difficulties and present first promising results.

Index Terms— Bioengineering, Biomedical signal processing, Korotkoff sounds, HMM

1. INTRODUCTION

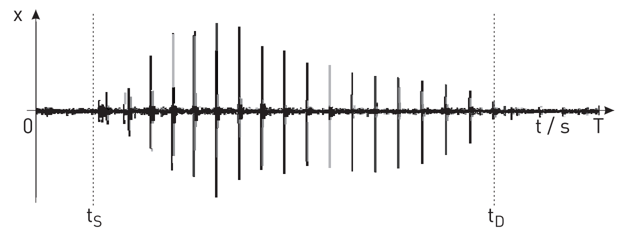
The non-invasive auscultatory method is one of the most common ways of measuring the blood pressure. It is based on the so called Korotkoff sounds (named after the discoverer [1]) which are caused by blood flowing through compressed arteries. While this method works very well when the subject is at rest, the interfering sounds of muscles and joints cause difficulties when applying it during sports and fitness activities. There is an alternative non-invasive method, the oscillometric measurement. However, it is also susceptible to movement of the subject [2, 3].

This paper describes a study in which we tried to apply the auscultatory method in combination with suitable signal processing and classification algorithms for active, moving subjects. Figure 1 illustrates nature and degree of interference by movements of the subjects during the measurement. Figure 1a shows a typical Korotkoff sound at rest, figure 1b a typical sound during some exercise.

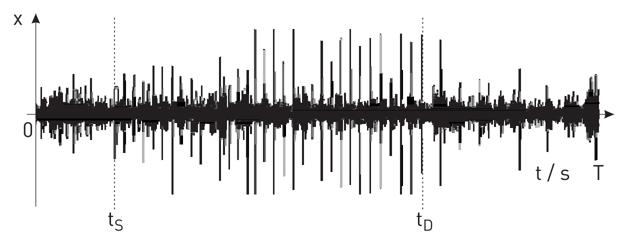
2. METHOD

2.1. Auscultatory blood pressure measurement

There are two blood pressure values to be measured: the systolic pressure (which is the maximum pressure exerted by the blood against the vessel walls) and the diastolic pressure (which is the lowest pressure between two successive heart beats).



(a) At rest



(b) During exercise (lifting a barbell while rolling the forearm)

Fig. 1. Typical Korotkoff sounds.

A pressure cuff is wrapped around the patient's upper arm and pumped up until the brachial artery collapses and there is no flow of blood through the artery anymore. Then the cuff pressure is slowly decreased until the blood in the artery resumes its normal (laminar) flow. Between the systolic and diastolic pressure there is a volatile blood flow in the vessel whose turbulence causes the Korotkoff sound. This sound can be heard placing a stethoscope at the patient's hollow of the elbow. Figure 2 shows the brachial artery and cuff pressures evolving over time. In the grey areas the blood pressure is greater than the cuff pressure and blood is spurting through. It is generally accepted that there are five phases of the Korotkoff sound which, according to [4], can be described as follows:

- Phase I: a tapping sound,
- Phase II: a soft swishing sound,
- Phase III: a crisp sound,
- Phase IV: a blowing sound and

- Phase V: silence.

Above the systolic pressure the vessel is squeezed off and we cannot hear any flow sound as well. However, this is commonly not regarded as a Korotkoff phase.

The systolic blood pressure p_S is located at the beginning of phase I, the diastolic blood pressure p_D is located at the boundary between phases IV and V.

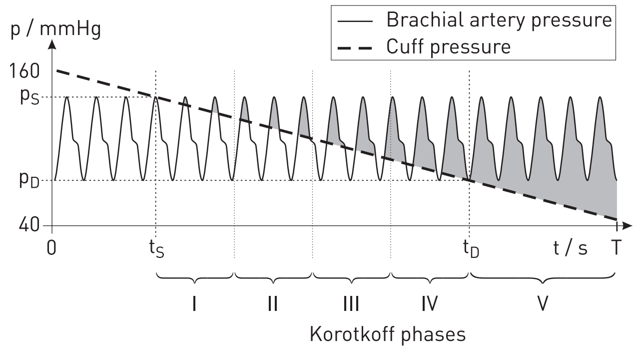


Fig. 2. Brachial artery and cuff pressure over time during a blood pressure measurement.

2.2. Technical setup

For recording the Korotkoff sounds we used a specially designed and patented device [5] which automatically pumps up the cuff to 160 mmHg and releases the pressure uniformly to 40 mmHg over a period of approximately 30 seconds. The Korotkoff sound is recorded by two microphones integrated into the cuff. The signals were digitized with 16 bits amplitude resolution and 1 kHz sampling frequency.

We recorded 289 Korotkoff sounds of 98 subjects. 169 measurements were done at rest, 120 measurements were done while the patients did exercises (lifting a barbell while rolling the forearm). The latter scenario is particularly difficult because this kind of exercise produces significant interfering noise in the Korotkoff sounds (cf. figure 1b).

In order to obtain training and reference data for the automatic measurement procedure we had an experienced nurse label the positions of the five Korotkoff phases in each recording. We played back the sounds through headphones and simultaneously supplied oscillograms as a visual aid. Precise labeling turned out to be a difficult task, particularly for the recordings disturbed by movements of the subjects. So we asked our expert additionally to estimate her degree of certainty on a four point scale from 1 (certain) to 4 (guessed) for each recording. The labels were set on the signals' time axis. Converting them to pressure values is straightforward as our device realizes a linear dependency between cuff pressure and time. So we compute the pressure simply as

$$p_{S,D} = \left(-120\frac{t_{S,D}}{T} + 160\right)\ \text{mmHg},$$

where T stands for the length of the recording (the signal offset always corresponds to a pressure of 160 mmHg, the end always to 40 mmHg).

The automatic measurement method we propose in this paper locates the phases of the Korotkoff sound in recordings as described above. This is a labeling task, pretty much the same as for instance automatic phoneme labeling of speech signals. We train one HMM for each Korotkoff phase plus one for the heading silence phase and then use these models to label recordings of Korotkoff sounds. From the positions of the labels of phases I and V we compute the systolic and diastolic blood pressure as described above.

In order to evaluate the performance of the automatic labeler we compare its labels to those set by our human expert. As a measure of correctness we use the absolute differences between the recognized and manually labeled systolic and diastolic pressures

$$\Delta p = |p_{S,lab} - p_{S,rec}| + |p_{D,lab} - p_{D,rec}|$$

where $p_{S,\cdot}$ and $p_{D,\cdot}$ stand for the systolic and diastolic, $p_{\cdot,lab}$ and $p_{\cdot,rec}$ for the labeled and recognized values. According to [6] we consider a measurement as "correct" if $\Delta p \leq 20$.

2.3. Feature extraction

Korotkoff sounds are mainly characterized by a sequence of pulses of high energy (which correspond to the heart beats). This suggests using correlation and energy based features rather than the usual spectral ones. We used analysis windows of 3000 samples (3 seconds) with an overlap of 2 seconds. For normal pulse frequencies of 60 beats per minute and higher each window contains at least three heart beats.

We studied several analysis methods in the time and frequency domains comprising a 200 channel amplitude histogram, a 3 channel amplitude crossing histogram, a 100 channel autocorrelatogram, RMS, zero-crossing density, LPC square error and an 8 channel cepstrum. This results in a 314 dimensional feature vector. As the dimension is by far too high for robustly estimating Gaussians we reduced it by keeping only the 11 first vector components after a principal component analysis. This feature set is called MIX1 in the following.

Secondly we hand-tuned a heuristic feature set MIX2 as follows:

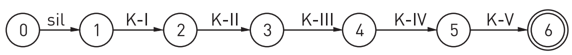
1-2	Means of the autocorrelation function for $0 \leq \tau < 0.6$ and $0.6 \leq \tau < 1.2$ seconds
3-4	Means of amplitude histogram bins $0.2 \leq \lvert x\rvert < 0.6$ and $0.6 \leq \lvert x\rvert < 1$ ($\lvert x\rvert$ is < 1)
5-6	Means of amplitude crossing histogram bins $0 \leq \lvert x\rvert < 0.011$ and $0.013 \leq \lvert x\rvert < 0.061$
7	RMS
8	Zero-crossing density
9	Linear prediction square error
10-11	Mean of cepstral coefficients $0 \leq q < 0.6$ and $0.6 \leq q < 1.2$ seconds

Finally we computed the first and second order difference features of MIX2 and reduced the resulting 33 dimensional vectors again to 11 dimensions by means of a principal component analysis. This feature set is called MIX2Δ in the following.

As a baseline feature extraction we computed a 1024-point-FFT with non-overlapping windows of 1 s length. The resulting feature vector was also reduced to dimension 11 through PCA to ensure a "fair" comparison.

2.4. Modeling and locating the Korotkoff sound

As described above, the recording of one auscultatory blood pressure measurement comprises six signal phases, a heading silence phase followed by the five Korotkoff phases. So we have a very simple regular grammar which can be represented by the following finite state machine $\mathcal{G}$:



With our signal classification system [7] we tested four HMM topologies as shown in figure 3. The examples are all models of Korotkoff phase I (label K-I). We always used identical topologies for all models (sil and K-I through K-V).

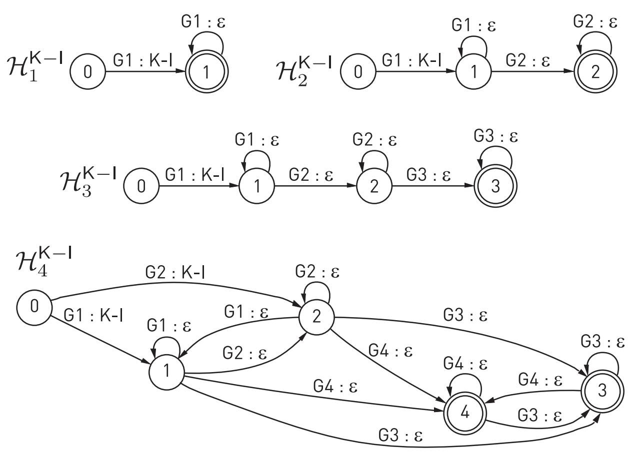


Fig. 3. Tested HMM topologies $\mathcal{H}_1 \ldots \mathcal{H}_4$. Gn denote Gaussians associated with the transitions.

The HMMs were trained from a set of 272 recordings by an EM estimation (Viterbi training). The remaining 17 recordings were automatically labeled. There was exactly one Gaussian per HMM state and we used full covariance matrices.

The decoding network $\mathcal{R}$ for the HMM labeler is:

$$\mathcal{R} = \left(\mathcal{H}_n^{\mathsf{sil}} \oplus \mathcal{H}_n^{\mathsf{K-I}} \oplus \ldots \oplus \mathcal{H}_n^{\mathsf{K-V}}\right)^* \circ \mathcal{G}.$$

The alignment of the signals on this network was done by the Viterbi algorithm and the blood pressure values were calculated as described in 2.2. Figure 4 shows an example for the result of the automatic labeling.

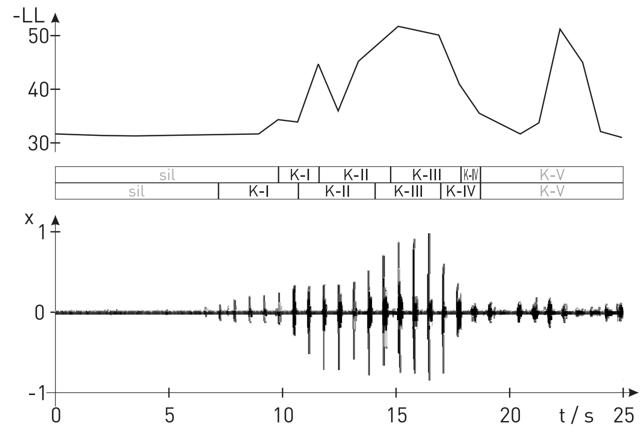


Fig. 4. Automatic labeling of a Korotkoff sound (bottom of figure). The second channel from the bottom shows the labeling result, the third channel the manually set reference labels. The upper channel shows the neg. log-likelihood scores computed for the respective signal segments.

3. RESULTS

We performed a leave-one-out cross validation (where "one" stands for one set of 17 recordings) to obtain automatic measurement results for *all* data.

First we conducted an experiment investigating the feature sets described in section 2.3. Throughout this experiment we used HMM topology $\mathcal{H}_1$. The results are summarized in table 1. We also tested a reference case where training and test data were recorded when the subjects sat still. This corresponds to the situation at the medical practice. The second scenario – mixed signals at rest and during exercise – is the realistic one for our application. The results show that it is by far the more difficult task, too.

HMM:	Topology $\mathcal{H}_1$				
Trained:	rest		mixed		
Tested:	rest	active	rest	active	mixed
MIX1	63.3 %	14.2 %	17.0 %	12.7 %	15.2 %
MIX2	72.2 %	25.8 %	63.7 %	28.0 %	49.1 %
MIX2Δ	-	-	**65.1 %**	**30.8 %**	**51.2 %**
FFT	64.5 %	6.7 %	47.4 %	17.8 %	35.3 %

Table 1. Correctness ($\Delta p \leq 20$) depending on feature set. Models were trained on signals recorded at rest and on a mixed set of signals recorded at rest and during exercise. Correctness was assessed for signals recorded at rest only, during exercise only and with a mixed test set.

Though there's obviously plenty of room for optimization, we can state that

- the heuristic feature set MIX2 clearly outperforms both, the automatically selected (MIX1) and the baseline FFT features (we can achieve even a little further gain introducing delta features MIX2Δ),

- it does not make any sense to try labeling recordings of active subjects with models trained with signals at rest (3rd column),
- training models with a mixed signal set decreases the performance for signals at rest significantly (column 2 vs. 4).

In a second experiment we tested the performance of the HMM topologies introduced in section 2.4. Here were consistently used the MIX2Δ feature set. Table 2 summarizes the results.

Feature set:	MIX2Δ		
Correct when:	$\Delta p \leq 20$		
Trained:	mixed		
Tested:	rest	active	mixed
$\mathcal{H}_1$	65.1 %	30.8 %	51.2 %
$\mathcal{H}_2$	76.7 %	32.5 %	58.8 %
$\mathcal{H}_3$	70.3 %	**41.0 %**	58.5 %
$\mathcal{H}_4$	**79.1 %**	37.6 %	**62.3 %**
Correct when:	$\Delta p \leq 30$		
Trained:	mixed		
Tested:	rest	active	mixed
$\mathcal{H}_1$	79.1 %	43.6 %	64.7 %
$\mathcal{H}_2$	87.8 %	58.1 %	75.8 %
$\mathcal{H}_3$	88.4 %	58.1 %	76.1 %
$\mathcal{H}_4$	**90.7 %**	**62.4 %**	**79.2 %**

Table 2. Correctnesses $\Delta p \leq 20, 30$ depending on HMM topology. Models were trained on a mixed set of signals recorded at rest and during exercise. Correctnesses were assessed for signals recorded at rest only, during exercise only and with a mixed test set.

In general we can say: the more complex the HMMs, the better the performance. Model complexity is, however, limited by the amount of training data (which was quite small in our tests). In the realistic scenario (column 4) we can achieve 62.3 % correctness.

4. CONCLUSION

We proposed a method of auscultatorily measuring the blood pressure using an HMM-based labeler. Even though the results are not yet satisfactory, we were able to proof the suitability of the method.

Investigating the problems we loosened the condition of correctness to $\Delta p \leq 30$ (lower part of table 2). That means the automatic labels may now deviate from the manual ones at most 15 mmHg in average of systolic and diastolic pressure. Under these circumstances we achieve a 17 % absolute higher correctness on the mixed test set. Particularly the correctness for recordings of active subjects rises drastically by 21 % absolute (column 3). It seems to be intuitively clear that interfering noise makes it much harder to precisely locate the beginning and end of the Korotkoff sound which are both characterized by low pulse energies (cf. figure 1).

But this is true for the human labeler as well. Especially for the noisy signals our expert often rated her own decisions as uncertain (see section 2.2). In instances like shown in figure 4 it's hard to tell whether the human or machine was more "precise". So we must assume that the manual setting of the reference labels was a drawback of the study. In future work we will assess the reference by an invasive measurement method which gives precise data or, at least, we will employ several experts for reference labeling. This gains even more importance considering that the uncertain reference labels were also used training the HMMs which might have compromised the models.

5. REFERENCES

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