A Control Cycle for the Automatic Assisted Positioning of Auscultation Sensors

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Abstract: The correct positioning of wearable biomedical sensors is crucial in the use of any automatic measurement systems. The effects of an inaccurate positioning can compromise the quality of the acquired vital waveforms, like phonocardiograms, and can make ineffective any healthcare application which uses wearable sensors. To solve this issue, this paper proposes an innovative control cycle for a control cycle to assist patients during the positioning of an auscultation sensor, a digital stethoscope, for a healthcare monitoring application. The control cycle runs on a user-friendly app and, through the use of a smartphone camera, suggests the auscultation sites overlapping the active camera view. In this way, the patient has a real-time feedback to ensure the correct positioning of the sensor.

1 INTRODUCTION

The increasing availability of wearable technological resources, computationally competitive and at a moderate cost, makes the realization of mobile computer-aided analysis and diagnosis systems more and more possible.

Biomedical sensors, integrated both in commercial and prototypal monitoring solutions, are commonly used in a lot of telemedicine applications in heterogeneous application domains (Patel et al., 2012). The growth of technology in integrated circuits manufacturing has brought huge innovations in embedded and portable sensors and has opened new interest in emerging application areas like ubiquitous computing and pervasive monitoring (Wickramasinghe, 2013). Examples can be found in several scientific papers, such as (Black et al., 2004) and (Hayes et al., 2007).

Due to their specific characteristics, healthcare systems, for continuous and non-invasive monitoring of vital parameters and biomedical signals, have consolidated their effectiveness through the use of wearable sensors and through their integration with Health Information Systems (HIS). These kinds of sensors, through the possibility they provide of acquiring data also during daily behaviour, are highly flexible in the realization of clinical applications for various patient profiles according to the individuals' different characteristics and lifestyles.

In general, during the use of wearable sensors, such as the auscultation sensors which we are going to discuss, their accurate positioning is an indispensable operating condition to ensure a high fidelity of the acquired signal and, consequently, to guarantee a high-quality analysis. Accordingly, any automatic measuring system that makes use of wearable sensors must take into account this consideration as an important requirement. In fact, the quality of a biomedical measurement depends both on the sensor sensitivity and also, principally, on how the patient applies the sensor.

In the case of a self-monitoring system, it becomes crucial to consider a control cycle that helps the patient during the measurements by suggesting the correct positions of the auscultation sites. Hence, the idea of focusing the interest of this research study on the design of an intelligent control cycle to assist the patient before starting the measurements and during the signal acquisitions.

This control cycle, embedded in a mobile real-time auscultation system, helps the patient during his/her self-auscultation session at his/her own home without any support from physicians. He/she follows the visual hints presented by the application to start and to guide the health monitoring session. If there is any active interaction with a remote physician, the control cycle can help to set the proper conditions for

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a tele-auscultation service and respects the commitment of promoting patient autonomy in the safeguarding of the right to health.

With these intentions, in order to promote widespread checks for a large catchment area, we have chosen to implement the control cycle on mobile devices, like smartphones or PDAs, taking advantage, as we are going to describe, of their hardware, in terms of interaction and calculation resources.

In summary, the paper investigates the theoretical and practical conditions, and proposes a control cycle for the assisted positioning of wearable sensors, in order to help the self-monitoring of vital functions in any auscultation system.

In the rest of the paper, we will introduce the background in section 2 and the state of art with its related works in section 3. In section 4 we will present the proposed control cycle with the details of the resources and the design choices made. Hints about its usability and considerations relating to improvements and performance evaluations will be discussed in section 5, in which will be also presented new ideas for future developments and perspectives. Finally, section 6 completes the paper.

2 BACKGROUND

The positioning of sensors, like ECG electrodes or auscultation sensors for heart or lung sounds monitoring, is commonly supported by the medical staff who assist the patient during the examination and guarantee the accuracy of the monitoring session.

For a healthcare service remote from the presence of clinical staff who can oversee the examination, for example in a remote auscultation solution where the patient is alone at his/her own home, it becomes necessary to consider a supporting control cycle for the sensor positioning that ensures the quality and the accuracy of the acquired signals.

The problems related to a positioning logic are due to the fact that the position of the sensor at the time of the examination can not be determined without considering a reference system with respect to which it is possible to evaluate that position. Therefore, it is useful to make use of an external system that observes the changes and tracks the positioning of the stethoscope over time. This observation sensor could be an image sensor embedded, for example, in a digital camera of a smartphone.

The idea is to suggest to the patient the auscultation sites by displaying to him/her, overlapping with the current active camera view, a map of the Regions Of Interest (ROIs) dynamically calculated with computer vision algorithms. The control cycle will be able to recognize the body shape of the patient with a shape matching algorithm using both chest and back anatomical models, and a shape transformation in order to redraw the ROIs from the model.

The following section explores the computer vision concepts used in heterogeneous environments that we have selected to solve the presented problem. We have inspected several possible solutions to choose the most appropriate approach.

3 STATE OF ART

Over the last few years, thanks to the theoretical consolidation of digital signal processing techniques and their implementations, there has been a growing interest in emerging trends that include the interpretation of optical and radar images for earth monitoring, character recognition in natural language (Pathak and Singh, 2014), medical image processing for automatic diagnosis, and motion tracking for surveillance systems. However, all these applications solve their tasks by adopting domain-independent algorithms.

In (Thijs et al., 2007) a technique for positioning sensors for acquiring vital parameters of a subject is presented. The method is based on a reference signal and a Doppler radar device to acquire a reference body signal representing a movement of an object within the subject's body, the position of the Doppler radar acquisition device being associated in a defined way with the position of the sensor, and storing the acquired reference body signal by means of a data storage device.

In applications in which object recognition is required, the most common methods use edge-based shape detection methods, or adopt a probabilistic approach to realize an adaptive shape selection.

(Yang et al., 2010) introduce a multi-scale shape context descriptor to model human body shapes and measure their similarity in different scales with respect to a predefined human body prototype.

(Hu et al., 2006) present a color-based method for torso detection in presence of different clothing and cluttered backgrounds. It extracts the torso by using a color probability model based on the analysis of the dominant colors.

Another very interesting paper is (Kumpituck et al., 2009) in which the authors present a stereo-based vision system that is used to determine the stethoscope location on the human body in a cardiac auscultation tele-diagnostic system. The reconstruction of the points in the three-dimensional space has been achieved by using a knowledge of the camera calibration, image rectification, epipolar geometry, and disparity computation.

When there is a stream of moving images, the target tracking becomes more challenging. In this field, the computing time plays a decisive role in the detection process. To ensure the real-time property, it is necessary to have fast algorithms that can return results on time in order to monitor the environment without any interruptions or delays.

In a visual surveillance service it may be useful to detect, track and recognize, in real-time, moving vehicles and pedestrians. Moving cameras capture a changing background that complicates the foreground detection. For this purpose, the paper (Li et al., 2012) is very helpful. It presents a human shape descriptor to detect and track human movements from moving cameras.

In many systems, different open source projects are supporting the programmer in developing the required solutions. For example, the Open Source Computer Vision (OpenCV) library contains a set of computer vision functions for digital image processing, including edge detection algorithms, shape transformations, and face detection. A brief introduction to the OpenCV can be found in (Culjak et al., 2012).

The OpenCV API offers the possibility of manipulating the camera in real-time, to obtain a real-time visual feedback in order to monitor events and actions, also on mobile platforms. Many scientific papers and books are focusing on the development of systems for both academic and commercial use by using this library. Additionally, our proposed supporting control cycle uses OpenCV, which has helped us to solve the shape recognition problem with its camera API. The implementation uses the OpenCV4Android SDK.

4 THE PROPOSED CONTROL CYCLE

The proposed control cycle uses the hardware resources of smartphones and tablets to support the processing steps. The control cycle suggests the correct location of the auscultation sites through a visual feedback system by using only the rear camera of the mobile device, in the case of the back auscultation, or only the front camera, in the case of the chest auscultation.

The application draws the map of the ROIs overlapping with the current camera view with an adaptive control cycle that uses an edge detection technique and extracts the back/chest edge of the patient by shaping a reference anatomical model on the detected human back/chest.

To select the real human body edge, the control cycle implements a similarity model based on correlation measures with respect to the reference model.

Possible problems due to the noise introduced by the mobile devices camera sensor and by the discontinuity of the background have been taken into account and solved thanks to the use of digital filters designed to reduce the spurious contributions that can interfere with the body edge detection.

The figure 1 depicts a high-level schema to illustrate how the proposed control cycle draws the ROIs on the active camera view.

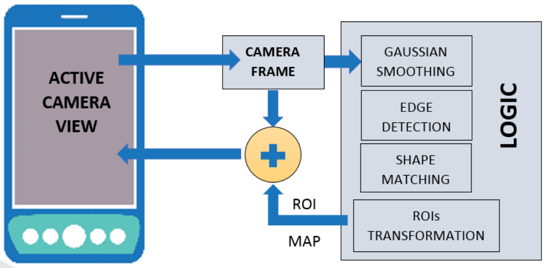

Figure 1: High-level schema for drawing ROIs.

The processing chain uses the following steps, illustrated in detail in the next sub-sections of the paper. In summary, the proposed control cycle:

1. captures the raw camera frames and filters each frame with a *Gaussian smoothing filter*;
2. uses an *edge detector* to extract the multiple edges from the filtered frames;
3. chooses, from the various edges, the only one corresponding to the real human body edge applying a *shape matching algorithm*; and
4. *draws the ROIs* by adapting the information from the reference chest/back models for the detection of the human body edge.

The 4-step control cycle runs in an asynchronous task and notifies its results to the main task for the drawing of the ROIs. When the asynchronous task is completed, the main task updates the display with the information about the position of the calculated ROIs.

From the implementation point of view, the proposed control cycle is able to work in real time, with a low computational cost, and is runnable on mobile devices with limited resources. Functions computationally more complex are written in native code, C ++, and invoked on the Android platform through the Java Native Interface (JNI). For this purpose, the OpenCV library is useful for us in that it makes available a large set of computer vision functions written in C++ ready to be used.

4.1 The Gaussian Smoothing filter

Starting from the raw frame acquired by the mobile device camera, the grey-scale converted frame is processed with a *Gaussian Smoothing filter* in order to reduce the background noise that is included in the acquired image.

Moreover, due to the geometrical discontinuities of objects behind the foreground subject, there may be, in the output of the edge detector, multiple edges belonging to the background of the image. These spurious responses can introduce false positive and false negative detections and for this reason, the design of the filter must be realized with care to avoid, or at least to reduce, these problems.

In fact, without imposing any constraints on the usability of the application of which the control cycle is part, it is necessary to take into account the possibility of having various backgrounds for each situation. This can add, in the output to the detector, the presence of unpredictable spurious edges that makes the identification of the body edge, among all the detected edges, more complicated.

In the absence of a noise model valid in general, the background noise removal becomes very difficult in practice due to the unpredictable variability of the background. The most suitable solution, rather than breaking down this spurious noise, preserves the useful information in the foreground, or rather the chest/back area of the subject on which the control cycle has to map the regions of auscultation, the ROIs.

The filter performs an average of the pixels in the image on a number of points fixed by the kernel size parameter. The standard deviation of the filter defines the shape of the impulse response and the weights of the filtering mask.

In general, a digital image $a[m,n]$ described in a 2D discrete space is derived from an analogue image a(x,y) in a 2D continuous space through a sampling process that is frequently referred to as digitization.

The 2D continuous image a(x,y) is divided into N rows and M columns. The intersection of a row and a column is termed a *pixel*. The value assigned to the integer coordinates [m,n] with m=0,1,2,,M1 and n=0,1,2,,N1 is a[m,n].

Applying the Gaussian Smoothing filter, each output pixel value is set to a weighted average of the neighbouring pixels. The focal pixel receives the heaviest weight (having the highest Gaussian value) and neighbouring pixels receive smaller weights as their distance from the original pixel increases. This results in a blur that preserves boundaries and edges better than other, more uniform blurring filters.

The equation of the Gaussian Smoothing filter in two dimension is:

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{1}$$

where x is the distance from the origin in the horizontal axis, y is the distance from the origin in the vertical axis, and σ is the standard deviation of the Gaussian distribution.

Our choice for the default filter parameters is 9x9 pixels for the kernel size (K) and 3 pixels for the standard deviation (σ) both in the x-axis and y-axis directions. Anyway, the parameters are adjustable from the application interface.

Figures 2 and 3 show respectively the impulse response of the Gaussian filter in the x-axis direction and in the x-y image plane.

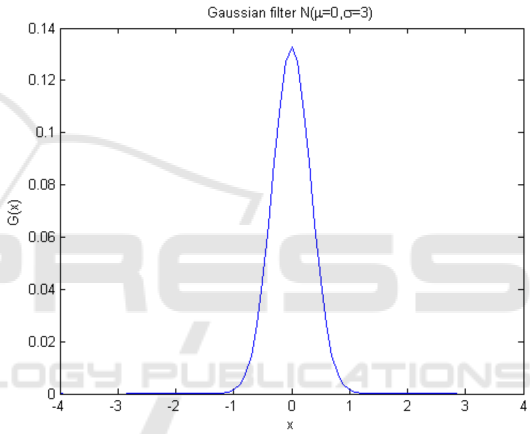

Figure 2: Normal distribution with $\mu = 0$ and σ=3.

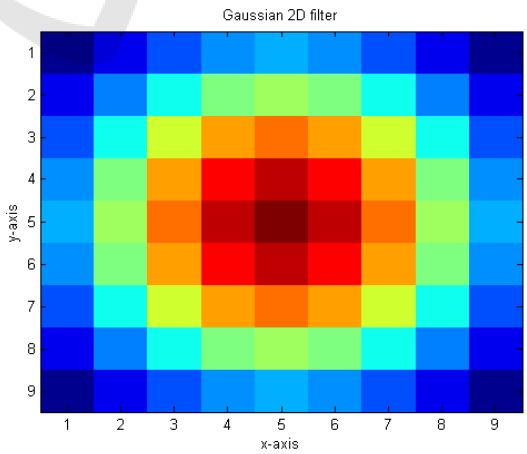

Figure 3: 2D Gaussian filter.

4.2 The Edge Detector

After the *Gaussian filter*, the smoothed frame is in the input to the edge detector to extract the edges.

The detector uses the multi-stage Canny algorithm (Canny, 1986), well known in literature as an optimal detector (Moon et al., 2002) due to its characteristics of low error detection rate, good edge localization and minimal response.

The process of the Canny edge detection algorithm includes these following steps:

- Application of a Gaussian filter to smooth the image in order to remove the noise;
- Finding the intensity gradient of the image;
- Application of a non-maxima suppression to get rid of spurious responses to the edge detection;
- Application of a double threshold to determine the potential edges;
- Application of a hysteresis threshold to suppress the weak edges not connected to the strong edges.

However, OpenCV implements the Canny algorithm without the Gaussian filter. The previous Gaussian Smoothing filter introduced in subsection 4.1 subsection covers the first step of the Canny implementation.

The C++ procedure receives as input the first and second thresholds for the hysteresis, the aperture size for the Sobel operator (Matthews, 2002) and a flag to calculate the image gradient magnitude as an L1 or L2 norm.

We calculate the gradient magnitude as an L2 norm, without any approximations, with a two Sobel convolution kernel of 3x3 pixels and two hysteresis thresholds set in the application preferences.

In the output to the edge detector, there is a greyscale image with multiple edges and, among these, the real body edge. The extraction of this single edge is performed by the *shape matching algorithm*.

4.3 The Shape Matching Algorithm

In the output to the *edge detector* we can observe an image in which all the false positives are external to the body region and scattered in the background. It follows that the extraction of the edge corresponding to the human body shape can be performed by selecting, among all the edges present, the one that fulfils a condition of similarity with respect to a model taken as a reference and placed in the foreground. The matching works from the inside of the foreground towards the outside of the background.

Several template-based matching techniques to find similarities among shapes have been explored in the literature. (Mahalakshmi et al., 2012) gives an outline of the general classifications of template or image matching approaches, which are the Template or Area-based approaches and the Feature-based approaches.

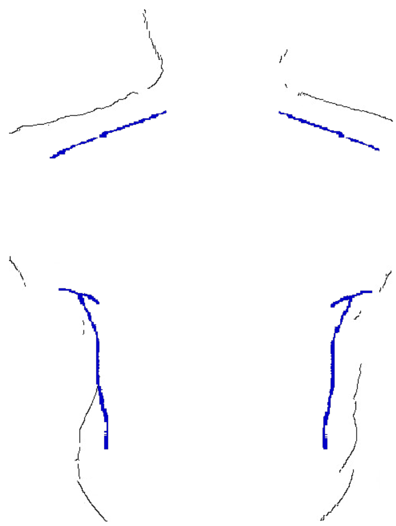

Figure 4: An example of an image obtained from the edge detector: the static reference anatomical model is visible in blue.

Nevertheless, in the current implementation of our control cycle, the similarity is estimated with a minimum distance criterion: among all edges, we choose the one for which the pixel-to-pixel distance is the minimum from a reference shape, in blue in figure 4.

In the output to the shape-matching algorithm, we have the unique edge that represents the chest/back shape useful for drawing the auscultation sites within it.

4.4 Drawing the ROIs

The positions where the ROIs are drawn are dynamically calculated on the basis of geometric information acquired from a reference anatomical model, a static information source, and adapted to the specific body shape of the patient, that is a dynamic information source.

An example of a static anatomical chest table is shown in figure 5.

We determine the dynamic map or ROIs associated with the dynamic edge of the human body by transforming the ROIs found in the static map of the model. The control cycle inspects the static model and looks for the ROIs. Then, it returns the central point of each ROI and applies a coordinate transformation to map the ROI coordinates from the model reference system to the human body edge detected.

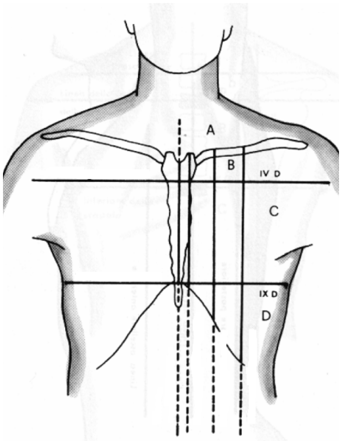

Figure 5: Reference body shape with ROIs.

The ideal transformation is a warping that calculates the new position of each pixel of the body edge for each pixel of the reference shape model before transforming the ROI coordinates. Due to its high computing time, we prefer to adopt an approximation by using two linear transformations working in cascade.

Therefore, the coordinate transformation, mathematically defined by equations (2) and (3), moves each point from the reference model to the human body edge by redrawing each ROI coordinate as shown in figure 6 that illustrates the geometry of the transformation.

$$\begin{cases} \frac{AP}{PB} = \frac{A'P'}{P'B'} & (2) \\ \\ \frac{CP}{PD} = \frac{C'P'}{P'D'} & (3) \end{cases}$$

The new coordinates of point P, the center of the ROI, are calculated as follows: first, the x-coordinate of the point is calculated with equation (1), and then the y-coordinate is calculated with equation (2) using the x-coordinate found through equation (1). The new coordinates of point P' are the result of geometric translations in the plane x-y that rearrange the points of the ROIs by preserving the proportions between the two shapes.

5 CONSIDERATIONS AND FUTURE WORKS

This section give a brief description of the proposed control cycle from the patients point of view during a self-auscultation session of his/her chest, and introduce new ideas for future developments.

Once the application is running, the patient positions himself/herself in front of the smartphone camera and can see his/her image in the active view on the mobile device display. He/she can choose to activate the assisted sensor positioning service, and after a few fractions of a second, the exact waiting time depending on the computing power of the smartphone used, he/she visualizes, overlapping with the active view, the suggestions about the ROIs.

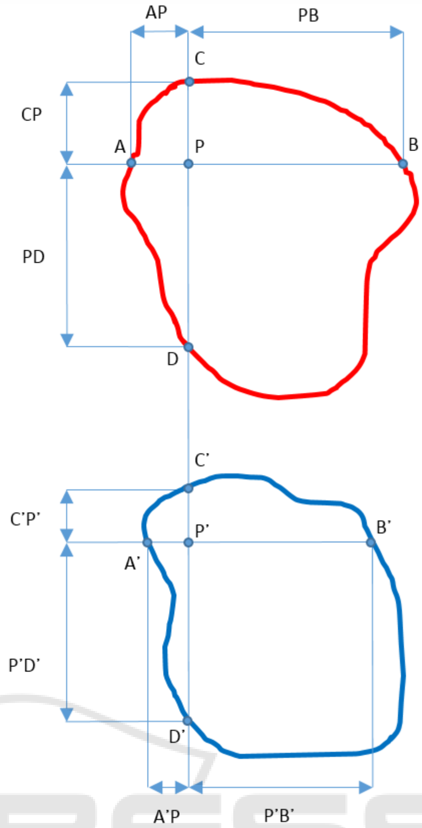

Figure 6: Point transformation from model to edge.

As we have already described, the control cycle runs on an asynchronous task which notifies the main task with the positions of the ROIs after a variable time. We recommend the user not to move during this time.

The proposed control cycle is based on a shape matching with a static shape and a dynamic adjustment of the ROIs through two linear transformations. A full dynamic control cycle, which does not require any constraint on the position of the user with respect to the static shape model, considers the replacement of the static matching block with a dynamic control cycle based on face detection. With dynamic shape positioning, the model will be shifted along the vertical axis in the plane of the camera view according to the shoulder level evaluated by the face detection results. With this new control cycle, the model dynamically fits its position to the current position of the user.

Possible improvements of the presented control cycle could involve the filtering and the shape matching algorithms. Other possible enhancements could be the adopting of spatially-variant filters to manipulate the selective properties of the smoothing filter for the noise reduction. In this case, the coefficients of the filtering mask depend on the location of the pixels in the input image. A theoretical formulation that faces with this issue and uses anisotropic diffusion is described in (Perona and Malik, 1990).

Finally, to improve the selectivity of the shape matching algorithm, we are considering to design specific static models taking account the gender and the different body types of the patients.

As regards the performance evaluation of the supporting control cycle, we are evaluating two different criteria. First, we are measuring the accuracy of the positioning, by checking the quality of the acquired waveforms in various tests. In relationship to this latter aspect, we are inspecting the regularity of characteristic parameters that could be calculated by the acquired waveform, the phonocardiogram, such as the average frequency and the information content of its power spectrum. Secondly, we are considering the usability of our supporting control cycle in terms of the time saved for each acquisition.

The usability test, together with the accuracy test on the waveform captured, will give us an important feedback on how our innovative control cycle tries to solve the sensor positioning issue in an automatic way.

6 CONCLUSIONS

Telemedicine, as a support for improving a patients quality of life, makes use of new solutions of non-invasive and continuous monitoring with wearable sensors.

The characteristics of these sensors help us to monitor the health of the patient by collecting more data during the day and the night. Behaviours and habits during the illness can thus be tracked and used to build a clinical profile more accurate for the patient. Additionally, the real-time acquisition of clinical data helps to build new Electronic Health Records of patients and gives the possibility to realize automatic analysis and diagnosis systems to promptly assist them.

As a support for the monitoring, this paper has introduced a new control cycle to meet the operational requirements of wearable sensors in an auscultation system. The control cycle assists the patient to select the right position of the auscultation sites on his/her own chest or back before starting the signal acquisition.

With use of a mobile device, such as a smartphone or a PDA, and its camera, the presented control cycle maps the Region Of Interests, corresponding to the positions of the auscultation sites, on the active camera view. In real-time, on the smartphone display, these visual hints are shown and the patient knows where he need to place the stethoscope. This is the initial condition to start a session to monitor the heart sounds, with front camera in self-monitoring mode, or to monitor the lung sounds, with back camera.

In the prospective of a medical tele-consulting service, the positioning logic will be part of the prerequisites of a real-time tele-auscultation application (Bellido et al., 2015).

The solution will extend the control cycle of its intelligent layer with the smart interaction of the camera, here proposed, to give the positioning feedback to help the patients.

Accordingly, at his/her own home, the patient will be able to enjoy an easier healthcare in ways and at times meeting his/her own requirements, in autonomy and independence.

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