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# COMPUTER APPLICATIONS TO ASSIST RADIOLOGY


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# Computer-Aided Selection of Window and Level for Filmless Radiology

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## 1. INTRODUCTION

Radiology is steadily moving towards a filmless environment [1, 2]. Computer workstations used in current PACS systems require radiology technologists or radiologists to modify the window/level settings to optimize the amount of clinically useful information that can be displayed using monitors which are currently limited to the display of only 8 bits of contrast data at a time [3]. This process is time consuming and can also be challenging for a technologist or radiologist and may be very difficult for clinicians utilizing the computer workstation. Additionally, certain types of CR images such as a foot CR typically have one window/level combination that is clinically best for evaluation of the toes, another window/level combination for the metatarsals, and still another for the hindfoot. The purpose of this study is to test the clinical efficacy of a computer algorithm[1] [4] designed to derive one or more optimal window/level settings based upon an analysis of image content for a computed radiography (CR) image.

The algorithm was sufficiently efficient to be able to suggest window/level combinations which correlated well with those subjectively determined independently by radiologists experienced in soft copy interpretation, and do so in about one second on a Macintosh Quadra 950 or Pentium 90 class computer workstation.

Manual optimization of window/level is time consuming, and, if performed incorrectly by a user not expert in soft-copy interpretation, it might result in a missed diagnosis or misdiagnosis. The algorithm that was tested increased the speed and accuracy of window/level optimization especially for an inexperienced user (the first author), and correlated well with the settings used by experienced

[1] This algorithm is the subject of a patent disclosure

radiologists. The routine incorporation of this algorithm as a workstation tool would increase productivity in a radiology department and would be expected to improve both image quality and time required for image review by less experienced users.

## 2. REQUIREMENTS ANALYSIS

Let us postulate a list of requirements for a computer-aided window/level control tool.

- The "optimal" choice of window/level strongly depends on the image itself. This implies that any reasonable decision for window/level settings should rely on image statistics.
- The "optimal" choice of window/level strongly depends on what the radiologist is looking for. This implies that, for any given image, there may not be one "best" choice of window/level, but rather *a set* of optimal choices.
- The tool should provide sufficiently many, yet not *too many* menu choices, for its purpose is to *aid* the radiologist in making proper adjustments by cutting down the search to a few optimal candidate settings.
- The tool should be available on-line and run in real-time. A radiologist experienced in soft-copy interpretation usually spends less than a minute to manually determine a proper initial window/level setting. It follows that the tool should run in the order of a few seconds in standard workstations used for image interpretation.
- The tool should be *generic* in that it should not be tied to any particular medical imaging modality and/or type(s) of study. The tool should be able to *learn* its parameters by observing the responses of a radiologist who uses it.
- The tool should *aid* the radiologist in quickly reaching a satisfactory window/level setting.

## 3. TECHNICAL DESCRIPTION

Most medical imaging modalities produce images of the spatial distribution of some indirectly measurable property of a projection or slice of the human body, e.g., tissue density in X-ray imaging. The very basis of X-ray imaging is that different anatomical structures, like bone and soft tissue, have very different densities, and, therefore, very different X-ray absorption patterns. This results in radically different intensity profiles for bone and soft tissue image regions. This difference also manifests itself in the histogram of the acquired X-ray, in which bone content and soft tissue content appear as distinct (albeit overlapping) lobes. In general, different kinds of anatomical structures typically manifest themselves as distinct but overlapping lobes in the histogram. However, noise as well as measurement errors and inconsistencies often make these lobes hard to distinguish and classify. As a result, the average medical image histogram is a multimodal profile, cluttered by background outliers, and noisy local extrema.

From the above, it follows that a reasonable approach would be to attempt to *segment* the given image histogram into a relatively small number of segments which correspond to features of potential interest, then for each such segment select a window/level of width equal to segment length, and centered at the midpoint of the segment.

This idea draws on earlier published work in [5] and some references therein, notably [6, 7, 8]. It differs in the following key respects: (i) In [5] and in earlier work the methods are task-specific, i.e., geared towards chest radiographs; thus (ii) in [5] the segmentation consists of a fixed pre-determined number of segments (actually, three). In addition, (iii) in [5] the segmentation rules are reasonable, yet heuristic. Finally, (iv) in [5] and [6, 7, 8] the resulting segmentation is not used to "drive" a window/level tool; instead, it is used to design look-up tables that emphasize soft or dense tissue. In contrast, our method is generic in the sense of being applicable to different modalities and exam types, and uses a variable number of segments, as needed for each application. It is rigorous and optimal [9], and uses the resulting segmentation to derive candidate optimal window/level settings. Nowadays, the window/level operation is by far the most popular interactive image enhancement technique among radiologists seasoned in soft-copy interpretation.

A radiologist typically starts by choosing window width, e.g., initially chooses a wide window to see the "big picture", then proceeds by choosing a narrower window to focus on some feature of interest. Too narrow windows are not desirable, for they lead to very coarse quantization using few grey levels, and this results in blocky, visually inferior image renditions.

Based on these observations, we may now proceed to pose histogram segmentation as a formal optimization problem, namely, one of optimally segmenting the histogram subject to a segment runlength constraint (this corresponds to a lower bound constraint on window width). This optimization has been posed and solved in a recent paper by Sidiropoulos [9], in the context of nonlinear filtering. The tool's operation can be summarized as follows:

- The user selects a region of interest (ROI). This may be the whole image, a part of the image, or a collage of several image parts. The user may also select $M$, the minimum width of suggested windows, or go with the system default, at her/his option.
- The computer computes the histogram of the ROI.
- The computer automatically optimally segments the computed histogram.
- For each segment of the resulting optimal segmentation (some segments may be discarded on the basis of prior knowledge), the computer suggests a corresponding choice of window/level, level being the segment's midpoint, and window width being the segment's width. In addition, the computer may also suggest window/level combinations corresponding to a union of two or more consecutive segments. The reason is that radiologists often choose multiple *overlapping* windows for viewing a given image.
- The user refines the suggested choices, as needed.

A suitable default value for $M$ is a function of individual preferences and imaging modality, and it can be adaptively "learned" in a PACS implementation. The entire process is best understood by means of an example.

### 3.1. DESCRIPTION BY EXAMPLE

Figure 1 depicts a typical histogram profile of some ROI. The resulting optimal segmentation along with one suggested choice of window/level are presented in figure 2. The first and the last of the suggested window/level choices are then discarded on the basis of prior knowledge (e.g., the first option is known to correspond to clinically irrelevant black background). The overall process runs in approximately one second on a Macintosh Quadra 950 or Pentium 90 class computer workstation. The resulting menu of choices (possibly refined by an experienced radiologist) may now be stored (with minimal overhead) along with other image header information, to facilitate viewing by others.

Figure 3 is a knee X-ray. Figure 4 depicts a computer-suggested view of the knee joint. The interested reader may peruse the following link on the Web:

`http://www.glue.umd.edu/~nikos`

and follow the link to *Computer-Assisted Selection of Window and Level for Filmless Radiology*, for a short technical description of the window/level problem, along with a suite of eight knee and foot CR's with invention highlights. These have been dithered to reduce transmission time (originals are 7.5Mbytes each); however, they still convey the basic idea.

## 4. CORRELATION WITH EXPERT OPINION

Nineteen CR's of eight patients from the VA Medical Center have been selected to test the proposed algorithm. These include chest, hand, knee, foot, shoulder, c-spine, L/spine, and abdomen images. This set was selected by an experienced radiologist to be representative of the typical range of images (some hard and some easy to window/level) that the radiologist might encounter when reading these radiographs.

Four radiologists experienced in soft-copy interpretation were each given four or five of the above images. For each one, they were asked (i) What would be an overall "best" choice of window/level; (ii) Provided they are allowed two "best" choices of window/level, what would these be? (iii) Provided they are allowed three "best" choices of window/level, what would these be? Note that, this being a small-scale experiment, no two radiologists were presented with the same image, although this may be of interest in assessing consistency across radiologists. Each one of the nineteen images in the test set was also processed by the proposed computer-aided window/level tool for various values of $M$, and the resulting window/level suggestions were recorded.

The analysis of the responses reveals some interesting points. It appears that, when asked to come up with a unique overall "best" choice of window/level, the participants consistently selected a combination that essentially captured all activity in the histogram, and potentially extended a bit more to the left and to the right. This is consistent with the requirement that such a unique combination strike a balance that allows the radiologist to see as much of the "big picture" as possible. It also coincides with the unique suggestion of our proposed tool for sufficiently large $M$.

It was also evident that, for a given number of allowed window/level combinations, the respective subjective optimal choices may overlap substantially; this is accounted for in the proposed tool by allowing window/level combinations corresponding to a union of two or more consecutive segments.

The overall conclusion is that the computer comes up with a set of window/level suggestions containing a subset that correlates well with the subjective (empirically determined) optimal ones, and then some more that do not seem to be perceptually relevant. The latter may be quickly discarded, and the ones that do correlate well may be further fine-tuned, as needed.

## 5. CONCLUSIONS

The algorithm that was tested increased the speed and accuracy of window/level optimization especially for inexperienced users, and correlated well with the settings used by experienced radiologists. The routine incorporation of this algorithm as a workstation tool would increase productivity in a radiology department and would be expected to improve both image quality and time required for image review by less experienced users.

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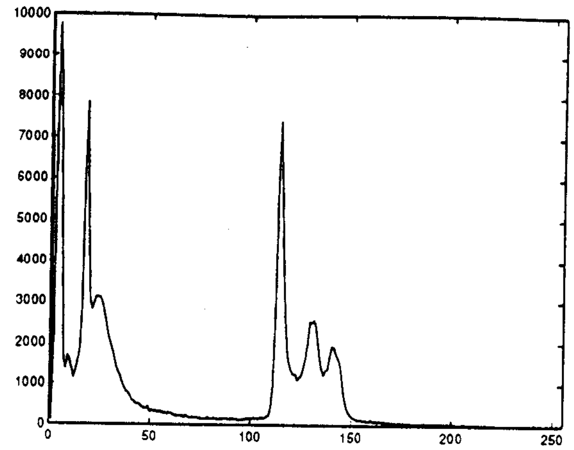


Fig. 1. Image histogram

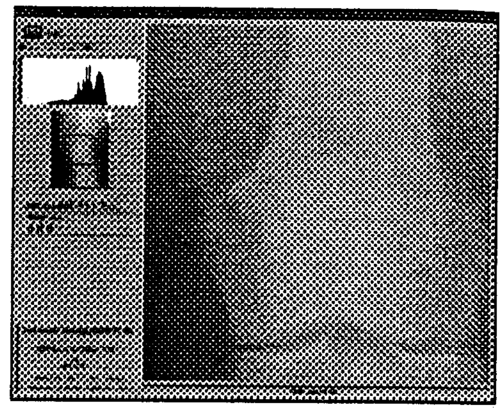

Fig. 3. A knee X-ray

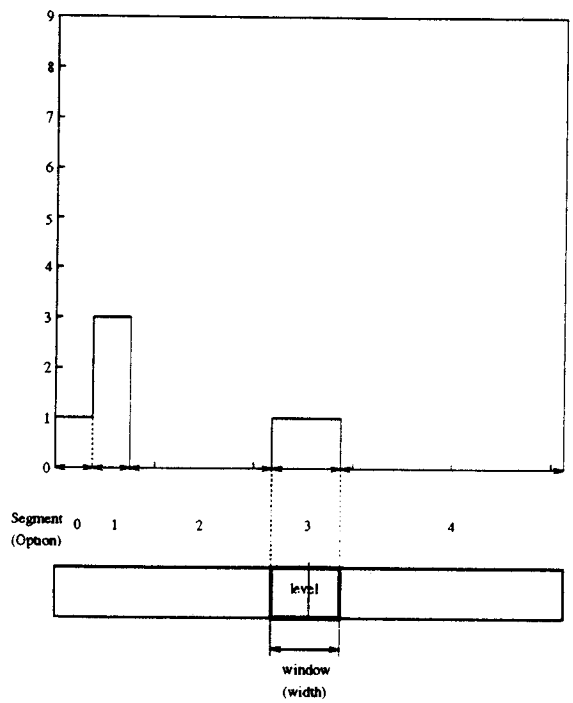


Fig. 2. Optimal segmentation, and one of suggested choices of window/level

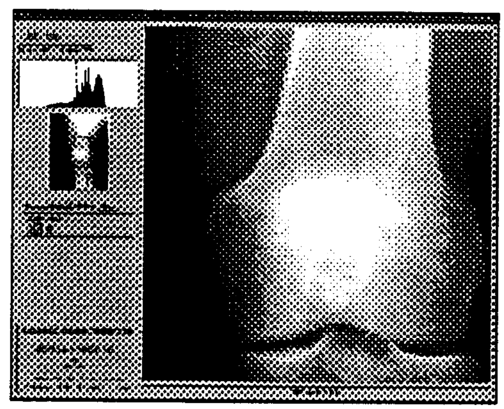

Fig. 4. Computer-suggested view of knee joint