Knowledge Engineering Issues for Footprinting Feature Extraction

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Abstract. This paper addresses knowledge engineering methodological issues concerning the integration of image processing techniques into a framework module for a foot classification expert system. The main problem is not just to build-up a module based on existing techniques but to test them on the new domain application so to produce a reliable and robust system. The paper introduces general issues concerning the process of knowledge engineering; it then presents results from the application of the methodology to implement a foot classification expert system based on image processing techniques. Results and experiments are described to demonstrate those issues mentioned.

1 Introduction

Research on image processing has developed a lot of techniques and algorithms, from image filtering process to image understanding methodologies [1–5]. However, when trying to integrate them into a single knowledge-based architecture some insight about knowledge domain has to be taken into consideration so to produce a reliable and robust system [6]. An example of an integration problem is the main-features extraction from footprinting. This paper addresses the main issues concerning the methodological aspects concerning the knowledge engineering process to deploy a foot classification system for the National Polytechnic Institute.

At the National Polytechnic Institute, a general medical diagnosis is carried out each year for incoming students at high school and superior levels. This diagnosis includes not only general health but also the determination of the foot type so to recommend proper therapies. Especially for students, who want to dedicate part of their studies to practice some sport, or those, who once finished their educational formation, will be dedicated to activities that require them to walk or to be stood most of the time, it is important to determine if they are physiological fit to perform those activities. Thus, an initial research was carried out to determine the best way to perform the foot classification considering the high volume of cases to be diagnosed. The conclusion was to build-up an automated system able to proper classify the footprint of approximately 40 thousand students. The next step was to propose a formal solution, which was the development of a computerized processing system to record, manage and perform the classification process with a minimum time response. The system was divided into two sub-systems:

A. Gelbukh, S. Suárez, H. Calvo (Eds.)
Advances in Computer Science and Engineering
Research in Computing Science 29, 2007, pp. 110-119

Received 29/06/07
Accepted 19/10/07
Final version 24/10/07

the management sub-system, which enables recording of digitalized footprints and the foot classification sub-system. The first one was treated as a normal information system facility applying conventional software engineering techniques while the second subsystem motivate a more in-depth research in which knowledge engineering techniques were applied [7].

The determination of the foot type implies a three-step process: firstly a podography or footprint is produced by means of walking through an inked paper; secondly the specialist looks at the footprint and mentally marks feature points on the podography, and finally those feature points are mentally measured and compared against foot-type parameters [8–11]. As a consequence, the research focused on devising a knowledge-based system, which extracts the feature points from the digitalized podography and performs the comparison against the foot-type parameters.

The paper summarizes the knowledge engineering process to determine the values of the foot-type parameters and the process to extract feature points on the podography. Some image processing techniques are described showing the suitability of use for the described problem. The next section describes the overall architecture of the foot classification system, explaining in detailed the image processing module. Some experiments are then described to show the reliability of the image processing module, which is expected to functionally work on the overall system in a near future. Finally some conclusions regarding future work are drawn.

2 Knowledge Engineering Methodology

The process of building-up a knowledge-based system implies two main phases: the knowledge acquisition and the knowledge modeling phase. Literature presents these two processes as part of the **KADS** methodology, which guides the deployment of knowledge-based systems [6, 12, 13]. Modern approaches differ on the description of the methodology in a way that the design phase is interpolated from the knowledge acquisition process to the knowledge validation one [6]. The present work was carried out following the second approach due to its flexibility to build not only expert systems but generally knowledge-based systems and figure 1 shows the knowledge engineering methodology.

2.1 Knowledge acquisition

As a result of reading the literature on orthopedics and following a series of interviews with a human expert, the knowledge elicitation phase produced an understanding that there are mainly three types of foot among students aged 15 to 18: normal, cave and flat foot [8–11]. The knowledge acquisition phase concluded with the steps to "scientifically" classify the foot into one of the three types. The steps are described as follow:

1. Identify the fifth metatarsial contact point (external contact), call it A,
2. Identify an external heel contact point, call it B,
3. Join points A and B to generate the line $\bar{AB}$,
4. Identify the narrowest arch zone, and mark a point C over the lateral side,
5. Trace a line from C to $\bar{AB}$, obtaining the longitudinal lateral arch,

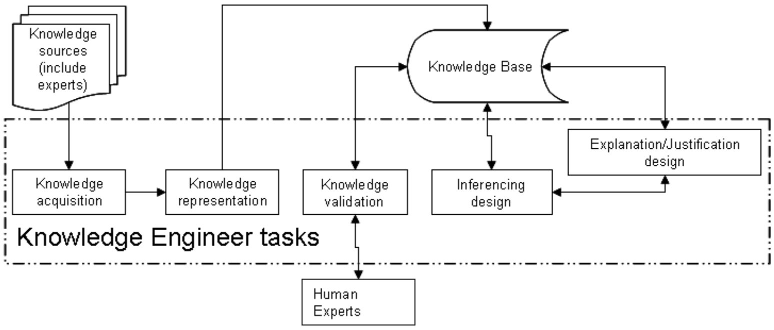


Fig. 1: Knowledge Engineering Methodology adapted from [6]

6. Identify the first metatarsial contact point (internal contact), call it D,
7. Identify an internal heel contact point, call it E,
8. Join points C and D to generate the line $\bar{CD}$,
9. Mark a point F over the internal side of the narrowest arch zone,
10. Trace a line from F to $\bar{CD}$, obtaining the longitudinal medial arch,
11. Measure the longitudinal lateral and longitudinal medial archs, and
12. Compare the measures against the foot-type parameters

The points and arcs are depicted in figure 2. The foot-type parameters were defined by the human expert as shown un table 1:

Table 1: Foot-type Parameters.

PARAMETERS	NORMAL FOOT	FLAT FOOT	CAVE FOOT
longitudinal lateral arch	5 mm.	$>$ 5 mm.	$<$ 5 mm.
longitudinal medial arch	$[15, 18]$ mm.	$<$ 15 mm.	$>$ 18 mm.

As a conclusion of the knowledge acquisition phase the foot classification method can be divided into two main process: a) the feature extraction, and b) the comparison process.

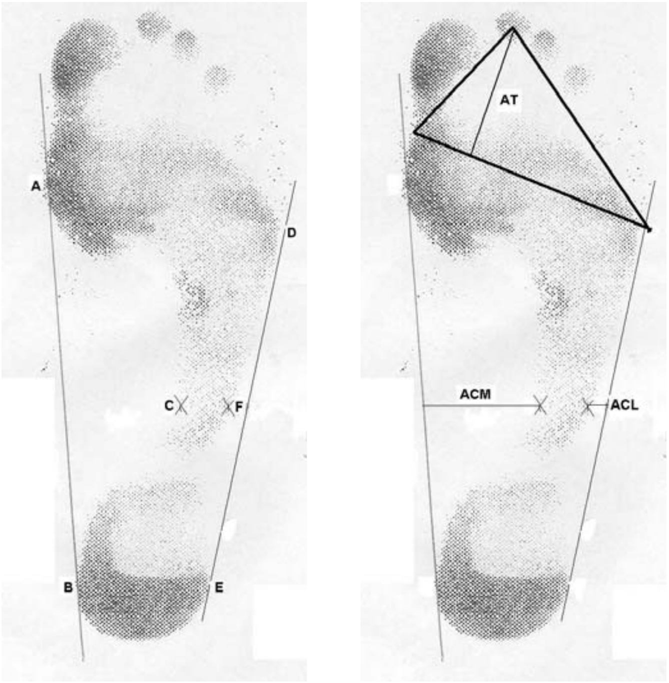
2.2 Knowledge representation

For the second process knowledge can be represented by a production system containing three simple rules:

1. If $LLA < 5$ and $18 < LMA$ then foot is a cave foot
2. If $LLA = 5$ and $15 \leq LMA \leq 18$ then foot is a normal foot
3. If $LLA > 5$ and $LMA < 15$ then foot is a flat foot

Where: LLA is the Longitudinal Lateral Arch and LMA is the Longitudinal Medial Arch.

Because the division of the method into process, some image processing techniques need to be applied. The next section revises some of the image processing techniques available for this problem.



(a) Characteristic points

(b) Arches

Fig. 2: Points needed to determine arches

3 Image Processing Techniques

Image processing comprises the set of algorithms intended to transform the input image in an understandable image. Several processes and techniques have arisen as a result of research and most of them have shown efficacy on getting good results. A common image process can be composed by the following tasks: a) the detection of a threshold value to differentiate the foreground from the background or to segment different regions of the image; b) edge detection to take away foreground pixels leaving only the contour of the objects; and c) feature extraction from edges, which depends on the domain knowledge and the application to be deployed.

3.1 Threshold Detection

This process is used when a thresholding operator needs to be applied and no threshold value is known. The thresholding operator selects pixels that have a particular value. It is useful for finding objects within an image, when the separation brightness is known. The thresholding operator can also be applied for region growing [1], and for segmentation, which results in a set of disjoints regions uniquely corresponding to objects in the input image [4]. When the latter is not known the value is determined by some the following methods: a) p-tile thresholding; b) methods based on histogram shape analysis; c) histogram concavity analysis; d) entropic; e) relaxation methods; f) muthithresholding [4]; g) optimal thresholding [5]; and h) iterative threshold detection [4], which was applied in the present work. The method was implemented following Sonkas algorithm [4] and was used together with a gray-level to binary conversion.

3.2 Edge Detection

According to [1] boundaries of objects tend to show up as intensity discontinuities in an image providing the principal motivation for representing objects by their boundaries. These boundaries are usually called edges and they can be located by applying an edge operator. Among the most applied edge operators, the canny operator is one of the most useful [3–5] because it can be applied under noisy conditions. This edge operator optimally operates by complying with three criteria: a) detection, b) localization; and c) one-response [3–5]. It is a gradient-based operator and it was implemented following Parkers algorithm as described in [3].

It was reported in [7] that under certain images conditions, several edge-points were not being closer enough as to form a solid region, the operator just produced a blurred image. As this result was not useful for the purpose of just determining the edge of the foot, other approaches were considered. The solution to the blurred image problem was found on the work of Rothwell et al about topological geometry, in which edge operators are defined following three properties: a) geometric information of the image to be processed; b) curve fitting to optimally guarantee a good edge; and c) recover of scene topology [14]. These findings made the work to focus on a more practical approach called digital morphology, which is a way to describe or analyse the shape of a digital object [3].

The main binary operator used was the dilator one followed by images subtraction. The dilation operator works over an image by enlarging objects belonging to the foreground as a result of applying a morphological structural element. The dilation operation can be formally defined, following [3] as: A dilation of a set A by the set B is $A \oplus B = \{c/c = a + b, a \in A \wedge b \in B\}$, assuming that A is the set of points defining an object on the image and B is the morphological structuring element. A more detailed description of the operator can be found on [3]. The implementation of the binary dilation follows [3] description.

From above follows the application of the subtraction operator to a couple of images: the result of dilating an image, images1 is subtracted from a double-dilated image, image2. Results in [7] showed that it was possible to produce an image in which only the edge of the objects appears.

It is shown that the iterative threshold detection, the conversion from gray level to binary and the edge detection using digital morphology provided a good means to foot image processing. Therefore, those were chosen to compose the architecture of the feature extraction module described in next section.

3.3 Feature Extraction

Feature extraction, in this case, is totally domain dependable; therefore, the procedure described before was implemented to find: firstly the characteristics points (A to G) and then three main arches. A first attempt was done by dividing the image in six uniform sections in which points might be found. After a careful revision, it was found that this approach did not considered all types of foot and thus, a second approach was attempted by dividing the image in eight uniform sections, which can be enumerated from 1 to 8 depending on the foot. This means if the foot being analyzed is the right one, section 1 will be allocated in the upper left square, and section 8 will be the lower right square; whereas, analyzing a left foot would implied that section 1 will be the upper right square and section 8, lower left one. Then, some assumptions need to be mentioned so the aforementioned procedure would be implemented: (i) Point A is located in section 1, at the nearest column from column 1; (ii) Point B is located in section 7, at the nearest column from column 1; (iii) Point C is located in section 5, at the column far away from column 1; (iv) Point D is located in section 2, at the nearest column from the maximum column of the image being analyzed; (v) Point E is located in section 8, at the nearest column from the maximum column of the image being analyzed; (vi) Point F is located in section, at the column far away from the maximum column of the image being analyzed.

It should be mentioned that the previous assumptions would work well on images clearly define and which comply with them. Experiments showed that the second approach improved the location of characteristics points. Measures of arches were computed applying basic concepts of analytical geometry such as distance of one point to a line.

4 Knowledge-based System Architecture

It was mentioned that knowledge based system give rise to not necessarily symbolic knowledge bases but usually to process of automatic data acquisition and small knowledge bases such as the one described earlier to classify digitalized foot images. In this way, an automatic foot classification system is composed by the following modules [7]:

1. A register keeping module which aims to register the digitalized images and serves to lunch the image processing module.
2. The image processing module aiming to extract the main features: the longitudinal medial arch and the longitudinal lateral arch. This module is composed by the following processes:
   (a) a format conversion from jpg to pgm, mainly to produce an image that can be processed faster;
   (b) the iterative threshold detector to find out the differential value between the foreground and the background;
   (c) an image conversion from gray level image to binary image as a means of decrementing the processing time;
   (d) the edge detection phase, which was further divided into double dilation and subtraction operations;

   (e) the feature extraction process, which results in a file containing the two main foot parameters.
3. The classification module in which the file with the two foot parameters is read and then a searching process is triggered to activate one of the three knowledge rules.

Figure 3 depicts the foot classification knowledge-based system, which works as follows: All the available foot images are registered into the system; after a period of time or a number of registered cases, each case includes both, the right and left, images; lunch the image processing module for each foot image, i.e suppose there are one hundred cases registered, the image processing module will be executed 200 times; as mentioned above, for each foot image the image processing module extract the longitudinal medial arch and the longitudinal lateral arch measures, which then are registered as part of the record of each case. After all the foot images have been processed, a flag is turn on and an alarm is switched on to announce end of this process. Finally, the operator or the user runs the classification module, in which parameters are red and compared against the knowledge base. This final process registers the foot types in the data base. After the completion of process, the user can print a report showing the results of the classification.

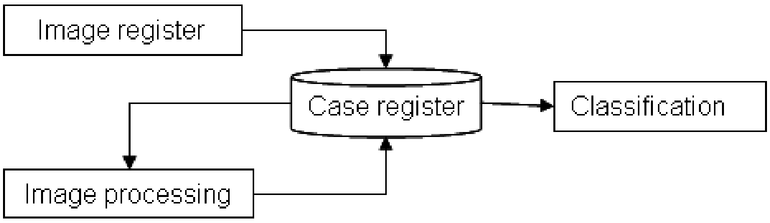


Fig. 3: Dilated image of a right foot

The image processing module, object of study on this paper, is shown in figure 4.

The decompression process was implemented following the graphics utilities installed with unix-like operating systems. The rest of the processes: threshold detect to feature extraction; were implemented in ISO C++. They were functionally and individually tested on WINDOWS.

5 Experiments

The overall image processing module was tested on a PC under SOLARIS system. Average time processing and parameters-extracted values were the main focus of experimentation. The number of digital podographies tested was 200, then; foot parameters were measured manually for comparison purposes and a manual classification was made in order to compare the data extracted against the knowledge base. The average time processing for each case was less than 1 second, so using this as a time processing estimation for 40 thousand images the worst processing time would be 20,000 seconds

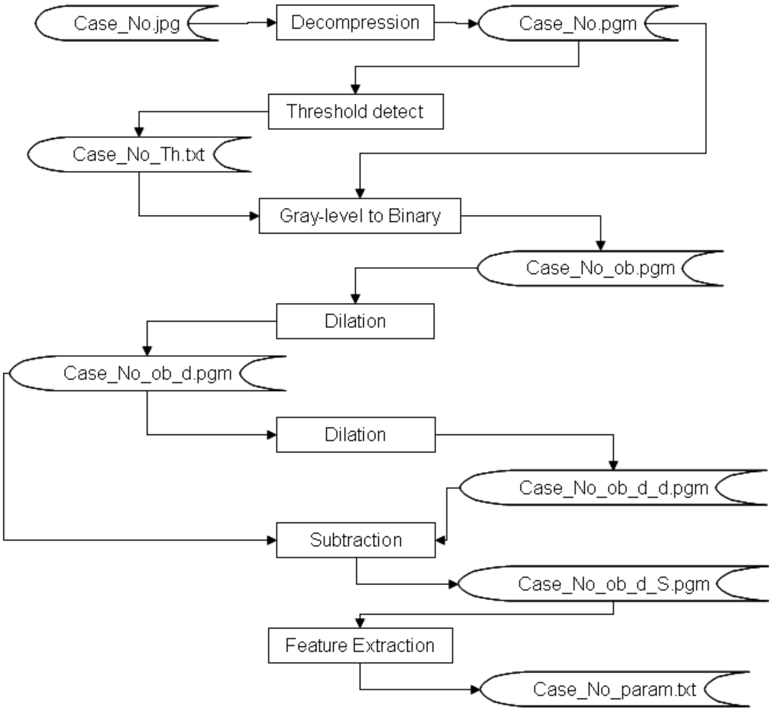


Fig. 4: Dilated image of a right foot

(or 5 hours) considering that the image process module runs sequentially for each image. The best case would be when the processes are run in parallel.

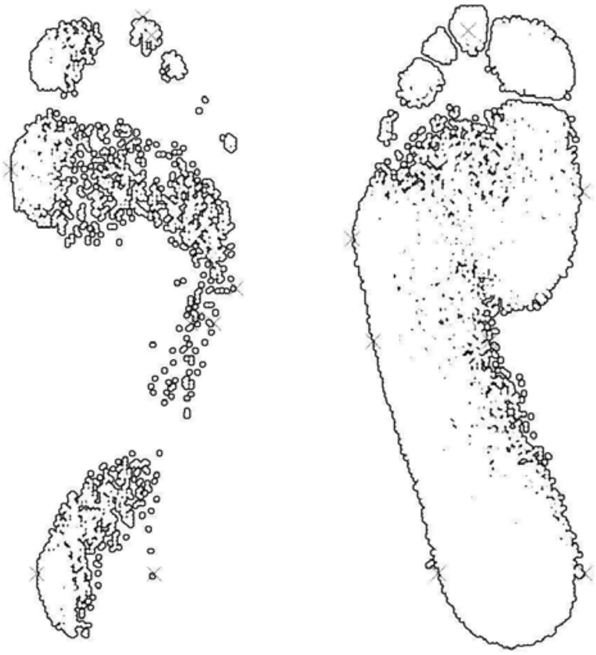
A comparison of values extracted automatically against the manual extraction showed up that the image processing module performed efficiently due to the computation of 95% of correct values. The remaining incorrect 5% was due to images do not complying with the underlying assumptions.

Figures 5 shows two digitalized podographies in which the process was applied:

Figure 5a shows the foot of case number 69, which has been classified as cave foot, whereas figure 5b shows left foot number 1597 classified as normal. Cross in all images mark important points to further extract the three main parameters. When comparing these measures against the knowledge base elicited from the human expert as explained above, the classification system asserts correctly their classification.

6 Conclusions

It was shown that image processing techniques need to be experimented before committing to one or some of them. Part of the knowledge engineering process also implied the refinement of knowledge, which also applied to refining the feature extraction process and consequently the image processing module. This refining stage started with the



(a) No 69: Right (b) No 1597: Left

Fig. 5: Two feet cases after the image processing module showing some marks

definition of having as a main part of the module an edge detection process based on conventional edge operators; however, as experimentation proofed, image morphology demonstrated its efficiency when combining simple operators like image dilation and addition. Further more, as the feature extraction process was based on an edge following algorithm, the process only focused on finding the important points (crossed points on figures 2 and 3) and computing both measurements using simple analytical geometry properties.

The knowledge engineering methodology shows that by assembling together the available and proper techniques, good results can be produced as shown in the experiments section. Also, it was shown that useful image processing techniques can be applied to images when they comply with special conditions and that further preprocessing need to be done in order to guarantee the proper extraction of features. However, at the moment of writing this paper, more testing was being carried out to guarantee the functionality of the system.

7 Acknowledgment

This project was sponsored by the IPN through the research projects program with register No 20060649. We also give thanks to the orthopedist, Rafael Ángel Matos y Santos as he was the human expert from whom knowledge was acquired.

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