UNIVERSITI PUTRA MALAYSIA

FULLY AUTOMATED BONE AGE ASSESSMENT USING BAG OF FEATURES ON HAND RADIOGRAPH IMAGES

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By

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Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfillment of the requirement for the degree of Master of Science

FULLY AUTOMATED BONE AGE ASSESSMENT USING BAG OF FEATURES ON HAND RADIOGRAPH IMAGES

By

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Chairman : Nasri Bin Sulaiman, PhD
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Bone age assessment (BAA) considered an essential task is performed on a daily basis in hospitals all over the world with the main indication being skeletal development in growth-related abnormalities. The manual methods for BAA are time consuming and subjective, which leads to imprecise and less accurate results. Thus, rendering the automated BAA more favorable. The purpose for BAA is to compare the measurement to chronological age so as to: Monitoring treatments and predict final adult height, observe the development for the skeleton and diagnose growth disorders, and to confirm age claims for children made by asylum seekers. Automated bone age assessment (ABAA) systems have been developed, none of these systems have been accepted for clinical use because there is a lack of agreement concerning the accuracy of bone age methods which is acceptable for a clinical environment. Most of the previously proposed methods for bone age assessment were tested on private x-ray datasets or do not provide source code, thus their results are not reproducible or usable as baselines. The previously proposed methods suffer from two main limitations: first, most of the methods operate only with x-ray scans of Caucasian subjects younger than 10 years, when bones are not yet fused, thus easier than in older ages where bones (especially, the carpal ones) overlap. Second, all of them assess bone age by extracting features from the bones either epiphyseal-metaphyseal region of interest (EMROIs) or carpal region of interest (CROIs) or both of them commonly adopted by the Tanner and Whitehouse (TW) or Greulich and Pyle (GP) clinical methods, thus constraining low-level (i.e., machine learning and computer vision) methods to use high-level (i.e., coming directly from human knowledge) visual descriptors. The analysis of bone age assessment becomes more complex when the bones are nearing maturity, when most of the bone would have merged, while some might overlap. The existing model-based approaches in the literature often reduce the region of interest (ROI) drastically to simplify the image analysis process, but this often leads to inaccurate and unstable results. Any system that attempts to automate skeletal assessment in an accurate

manner will need to consider the entire span of the hand radiograph. Reduced ROI leads to inaccurate and unstable results. This semantic gap usually limits the generalization capabilities of the devised solutions, in particular when the visual descriptors are complex to extract as in the case of mature bones. A novel machine-learning framework presented, aimed at overcoming these problems by learning visual features. The proposed framework is based on speeded-up robust features (SURF) combined with bag of features (BoF) models to quantize features computed by SURF. Support vector machines (SVM) are used to classify the simplified feature vectors, extracted from hand bone x-ray images. Overall 745 images were obtained, 472 images for males, 273 images for females, most of them belong to chronological ages centered around 15 to 18 years. The proposed framework allows achieving classification results with an average accuracy of 99%, mean absolute error 0.012 for the 17 years and 18 years for the male gender with the SURF and BoF approach. In the female model, the age range from 0 to 7 years are excluded, and in the male model from 0 to 8, because of the limited amount of data that obtained, the female model range starts from 8 years to 18 years with classification average accuracy of 82.6%. The male model range starts from 9 years to 18 years with classification average accuracy of 85%.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Master Sains

PENILAIAN TANAH AGUNG BANYAK YANG DIGUNAKAN MENGGUNAKAN CIRI-CIRI PADA RADIOGRAPH GAMBAR GAMBAR

Oleh

HAMZAH FADHIL ABBAS

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Penilaian Usia Tulang (Bone Age Assessment: BAA) dianggap sebagai tugas penting yang dibuat setiap hari di hospital seluruh dunia dengan indikasi utama di dalam pertumbuhan rangka berkaitan keabnormalan. Kaedah-kaedah asas untuk BAA mengambil masa dan subjektif, di mana ianya memberi keputusan yang kurang dan tidak tepat. Oleh itu, ianya menjadikan automasi BAA lebih baik. Tujuan BAA adalah untuk membandingkan pengukuran kepada usia kronologi supaya: Pemantauan rawatan dan meramalkan pengakhiran ketinggian dewasa, memantau pembangunan rangka dan mendiagnosis gangguan pertumbuhan, dan untuk mengesahkan tuntutan usia untuk kanak-kanak. Sistem Automasi Penilaian Usia Tulang (Automated Bone Age Assessment: ABAA) telah dibangunkan, namun tidak ada mana-mana sistem ini telah diterima untuk penggunaan klinikal kerana terdapat kekurangan persetujuan mengenai ketepatan kaedah usia tulang yang boleh diterima untuk klinikal. Kebanyakan kaedah-kaedah yang telah dicadangkan untuk penilaian usia tulang sebelum ini telah diuji pada set-set data x-ray peribadi atau tidak menyediakan kod sumber, oleh itu keputusannya tidak boleh dihasilkan atau boleh digunakan sebagai garis-garis asas. Kaedah-kaedah yang dicadangkan sebelum ini mengakibatkan dua batasan utama: Pertama, kebanyakan kaedah-kaedah ini hanya beroperasi dengan scan x-ray mata subjek Kaukasia lebih muda dari 10 tahun, ketika tulang belum bersatu, di mana ianya lebih mudah dari usia-usia yang lebih tua di mana tulang-tulang (terutamanya, tulang carpal) bertindih. Kedua, kesemua nilai tulang dengan mengekstrak ciri-ciri dari tulang-tulang sama ada kawasan berkenaan epiphyseal-metaphyse (EMROIs) atau kawasan berkenaan carpal (CROIs), atau kedua-duanya lazimnya digunakan oleh kaedah-kaedah klinikal oleh Tanner and Whitehouse (TW) atau Greulich and Pyle (GP), dan menghalangi kaedah-kaedah peringkat rendah (sebagai contoh, pembelajaran mesin dan penglihatan komputer) untuk menggunakan deskriptor visual tahap tinggi (sebagai contoh, datang secara langsung dari

pengetahuan manusia). Analisis penilaian usia tulang menjadi lebih kompleks apabila tulang-tulang hampir matang, ketika sebahagian besar tulang akan digabungkan, di mana sebahagiannya mungkin bertindih. Pendekatan berasaskan model sedia ada sering mengurangkan kawasan yang berkenaan (Region Of Interest: ROI) secara drastik untuk mempermudahkan proses analisis imej, tetapi ini sering menyebabkan keputusan-keputusan yang tidak tepat dan stabil. Mana-mana sistem yang cuba mengautomasikan penilaian rangka dengan cara yang tepat perlu mempertimbangkan keseluruhan tahap radiografi tangan. Pengurangan ROI menghasilkan keputusan yang tidak tepat dan stabil. Jurang semantik ini kebiasaannya menghadkan keupayaan generalisasi penyelesaian-penyelesaian yang dirancang, khususnya apabila deskriptor-deskriptor visual ini adalah kompleks untuk mengekstrak seperti di dalam kes tulang-tulang yang matang. Rangka kerja mesin pembelajaran novel yang telah dibentangkan, bertujuan untuk mengatasi masalah ini dengan mempelajari ciri-ciri visual. Rangka kerja yang dicadangkan adalah berdasarkan kepada ciri-ciri robust mantap (Speeded-Up Robust Features: SURF) yang digabungkan dengan model-model bag (Bag of Features: BoF) untuk mendapatkan kuantiti ciri-ciri yang dikira oleh SURF. Mesin-mesin vektor sokongan (Support Vektor Machine: SVM) digunakan untuk mengelaskan ciri-ciri vektor-vektor, telah diekstrak daripada imej-imej x-ray tulang tangan. Secara keseluruhan 745 imej telah diperoleh, 472 imej untuk lelaki, 273 imej untuk wanita, kebanyakannya tergolong di dalam kronologi sekitar 15 hingga 18 tahun. Rangka kerja yang dicadangkan membolehkan mencapai keputusan berklasifikasi dengan ketepatan purata sebanyak 99%, bermakna kesilapan mutlak 0.012 untuk 17 tahun dan 18 tahun untuk jantina lelaki dengan pendekatan SURF dan BoF. Dalam model wanita, julat umur 0 hingga 7 tahun telah dikecualikan, dan dalam model lelaki dari 0 hingga 8, ianya kerana jumlah data yang diperoleh terhad, julat model wanita bermula dari 8 tahun hingga 18 tahun dengan purata klasifikasi ketepatan 82.6%. Julat model lelaki bermula dari 9 tahun hingga 18 tahun dengan ketepatan purata klasifikasi 85%.

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This thesis was submitted to the Senate of the Universiti Putra Malaysia and has been accepted as fulfillment of the requirement for the degree of Master of Science. The members of the Supervisory Committee were as follows:

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This is to confirm that:

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LIST OF ABBREVIATIONS

AAM	Active Appearance Models
AUROC	Area Under ROC Curve
ABAA	Automated Bone Age Assessment
BoF	Bag of Features
BoSVW	Bag of Spatio-Visual Words
BoVW	Bag of Visual Words
RBF	Basis Kernel Functions
BAA	Bone Age Assessment
CROI	Carpal Region of Interest
CT	Computed Tomography
EROI	Epiphyseal Region of Interest
EMROI	Epiphyseal-Metaphyseal Region of Interest
FN	False Negative
GUI	Graphical User Interface
GLCM	gray-level co-occurrence matrices
GLRLM	gray-level run length matrix
GP	Greulich and Pyle Method for Bone Age Assessment
LBP	Local Binary Patterns
ML	Machine Learning
MSER	Maximum Stable Extremal Region
MSE	Mean Squared Error
MAE	Mean Absolute Error
NPV	Negative Predictive Value
PDM	point distribution model

PPV	Positive Predictive Value
RUS	Radius, Ulna and Short Bones
ROC	Receiver Operating Characteristics
ROI	Region of Interest
RMSE	Root Mean Square Error
SIFT	Scale-Invariant Feature Transform
SMS	Skeletal Maturity Score
SPM	Spatial Pyramid Matching
SURF	Speeded-Up Robust Features
SVM	Support Vector Machine
SRDM	Surround Region Dependence Method
TW	Tanner and Whitehouse Method for Bone Age Assessment
TP	True Positive

CHAPTER 1

INTRODUCTION

1.1 Background

The sum of time that a person has lived is Chronological Age, Bone Age, on the other hand, is the skeletal development of a person in the present time. Bone age assessment (BAA) is a skeletal maturity measurement of a person taking into account the normal population, it is performed in hospitals on a daily basis. The purpose for BAA is to compare the measurement to chronological age so as to:

- Monitoring treatments [1] and predict final adult height.
- Observe the development for the skeleton and diagnose growth disorders [2].
- Confirming age claims for children made by asylum seekers [3, 4, 5].

The procedure is performed by taking radiograph of the patient's non-dominant hand [1, 6, 7]. The reasons for using the hand in BAA are: first, it possesses a large amount of development in a small area; second, its exposes the subject to minimal amount of radiation comparing to other joints e.g. shoulder; and third, it is an easy area to radiograph. BAA is most commonly performed by using one of two methods: Greulich and Pyle (GP) [8] or Tanner and Whitehouse (TW) [1, 9, 10]. Greulich and Pyle method is the most frequently used for evaluation of skeletal age [11, 12] performed by clinician to compare the radiograph of a patient with a standard atlas of radiographs. They then decide which of the example radiographs is closest and assign the relevant age. The standard GP atlas is made up of radiographs from the mid-western United States from the 1930's and has been found not to be a good representation of modern populations [13, 14, 15].The TW method has been found to be more accurate than the GP method [16] however, it is used less frequently because it is more time consuming [12]. The bone age estimate obtained by one of these methods is compared with the chronological age to determine if the skeletal development is abnormal [17, 18, 19]. If a significant difference between bone age and chronological age exists, the patient may be diagnosed with a disorder of growth or maturation [7, 20]. The task of bone age assessment need to be automated as both GP and TW methods are time consuming [17, 21], the manual methods (GP and TW) are highly depends on the experience of the clinician/observer, resulting in significant inter- and intra- observer/clinician discrepancy [22, 23] making the task subjective leading to less accurate results. Tanner et. al. declared that “a computer could do better than a human operator” [1]. Bone age assessment test is done to differentiate chronological age and skeletal bone age [24], in order to assess hormonal and skeletal growth defects as well as their related problems [25]. Bone age assessment is difficult and time-consuming [23].The process of bone aging involves three steps:

A- The appearance and development of ossification for primary and secondary centers.
B- Growth of primary and secondary centers.
C- The time of fusion for both centers.

The development and growth processes involved in the steps have been identified [26], with the decision for BAA depends mainly on the time of fusion and ossification centers [27]. The assessment of chronological age is done by comparing and matching the radiographic images of a patients of known age and sex [16]. While the measurement of maturity is simply comparing the chronological age with the reference images [28], where the reference images were collected from variable sources, and presented as series called (atlas) [29]. Most of collected data that presented in atlases were gathered in longitudinal studies in the 1900s [30]. The gathered data was collected for anthropometric purposes in a standardized radiograph [31] hence the patient's data become references to estimate chronological age for educational and medical goal [14]. The development of children is strongly effected by nutrition habits and the environment [32], the data that formed the atlases were taken from healthy patients considered appropriate for standard uses [33], the images that shown in the atlases present maturity steps is a powerful source for age estimation [34]. In atlases, the matching process is done by comparing the most appropriate age instead of the maturation steps for recognized age [35]. The issue here is about relevant of atlases information with modern society and the usability with different era and races [36] which has been found not to be a good representation of modern populations [13, 14, 15]. Utilizing atlases presents images of known race with the maturation steps [37]. Although bone age assessment can be performed to different body bones like ankle, foot, shoulder, or clavicle [38] the left-hand wrist is used in the bone age assessment atlases [39,40], this because of risk of exposure to radiograph and the highly cost [41].

1.2 Motivation for Automatic bone age assessment

Automated bone age assessment (ABAA) has many advantages comparing with manual methods that used nowadays, in:

- assessments are more objective and therefore more likely to give the pediatrician more confidence in the diagnosis and course of treatment prescribed [22];
- it gives pediatricians more effective use of their time [42];
- it can be built upon radiographs from the local population and thus incorporate sociological and environmental factors [32]; and
- Manual methods are tedious and time-consuming and subjective [43],
- Most of the previous proposed automatic bone assessment methods are based on image processing algorithms leading to rejection of images that not met the proposed algorithm procedure [44].

- Hand bones are complex and overlapping therefore the previous proposed automatic methods were based on small number of bones causing in lack of efficiency [45].
- Automatic bone age assessment will help the pediatricians to achieve accurate and efficient diagnosis [46].

1.3 Problem Statement

Bone age assessment is a medical procedure to monitor skeletal development and to diagnose bone diseases, specifically, growth pathologies. As of today, it is carried out by visual inspection which is a tedious and time-consuming action [22]. Automated methods to carry out such a task are therefore desirable. The process of age estimation is the measure of the biological maturity transformed to chronological age by comparison with a reference data [28]. Reference data for the age estimation have been collected from healthy patients using the non-dominant hand from various resources and have been presented as a series called an "Atlas" [29]. Most of the previously proposed methods for bone age assessment were tested on private X-ray datasets or do not provide source code, thus their results are not reproducible or usable as baselines [47]. The previously proposed methods suffer from two main limitations: first, most of the methods operate only with X-ray scans of Caucasian subjects younger than 10 years, when bones are not yet fused, thus easier than in older ages where bones especially, the carpal bones overlap. Second, all of them assess bone age by extracting features from the bones either Epiphyseal-Metaphyseal Region of Interest (EMROIs) or Carpal Region of Interest (CROIs) or both of them commonly adopted by the TW or GP clinical methods, thus constraining low-level (i.e., machine learning and computer vision) methods to use high-level (i.e., coming directly from human knowledge) visual descriptors [48]. The analysis of bone age assessment becomes more complex when the bones are nearing maturity, when most of the bone would have merged, while some might overlap. The existing model-based approaches in the literature often reduce the ROI drastically to simplify the image analysis process, but this often leads to inaccurate and unstable results. Any system that attempts to automate skeletal assessment in an accurate manner will need to consider the entire span of the hand radiograph. Reduced ROI leads to inaccurate and unstable results. This semantic gap usually limits the generalization capabilities of the devised solutions, in particular when the visual descriptors are complex to extract as in the case of mature bones. A novel machine-learning framework presented, aimed at overcoming these problems by learning visual features, regardless of age ranges and races, that may facilitate the assessment process.

1.4 Aim and Objectives

The aim of this project is to propose a fully automated machine learning system for bone age assessment.

The objectives of this project are described below:

a) To create a novel system for bone age assessment using combination of bag of features with speeded-up robust features algorithms.
b) To reduce the system main absolute error and ensure accuracy through automation.
c) To create a specific database for Malaysian population considering nutrition habits and the environment.

1.5 Scope and Limitation

The study focusses on automation of bone age assessment using machine learning approach using the bag of feature method a novel framework is proposed. Fully automated BAA has been a goal of computer vision and radiology research for many years. Most prior approaches have included classification or regression using hand-crafted features extracted from regions of interest ROIs for specific bones segmented by computer algorithms. all prior attempts at automated BAA are based on hand-crafted features, reducing the capability of the algorithms from generalizing to the target application. Our approach exploits machine learning with bag of features to automatically extract important features from all bones in the image entirely as ROI that was automatically segmented by the bag of feature process. Unfortunately, all prior approaches used varying datasets and provide limited details of their implementations and parameter selection that it is impossible to make a fair comparison with prior conventional approaches.

While our system has much potential to improve workflow, speed and database, there are still limitations. Exclusion of 0–8 years in male, and 0-7 years in female, limits the broad applicability of the system to all ages. this limitation was felt to be acceptable given the relative rarity of patients in this age range. Another limitation is our usage of integer-based BAA, rather than providing time-points every 6 months. This is unfortunately inherent to the GP method. The original atlas did not provide consistent time points for assignment of age, rather than during periods of rapid growth, there are additional time points. This also makes training and clinical assessment difficult, given the constant variability in age ranges.

1.6 Contribution

The contribution of this thesis is: To present a novel framework for fully automatic skeletal bone age estimation system from X-ray image. This is a stage-based system and has the advantages that: an individual stage can be updated without affecting the other stages and that validation checks are performed after each stage. Furthermore, the assessments are based on robust features selection that is considering the hand entirely. The combine use of bag of features and speeded-up robust features were very successful in classifying objects in the radiograph and unaffected by position and orientation of the object in the image samples. The proposed framework achieved classification accuracy of 99% and main absolute error of 0.012.

1.7 Thesis Organization

Chapter 1 describe the introduction of the project. It describes the background, problem statement, aim, objectives, and contribution of this project.

Chapter 2 contains literature review regarding the project. It describes relevant image processing and machine learning techniques and previously proposed ABAA systems.

Chapter 3 contains methodology proposed in this project. We talk about supervised learning, data preparation and image database, normalization, speeded-up robust feature technique, bag of feature technique, support vector machines model, evaluating the performance of classification, and the importance of validation.

Chapter 4 contains results and discussion of the obtained results from the experiments. The database and normalization were shown. The training and testing were evaluated. The performance evaluation was shown.

Chapter 5 concludes what this project had achieved and some suggestion of future work.

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