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Enhanced Ocular Movement Analysis Through Deep Learning-Powered Image Processing

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Optomnology

Abstract:
Purpose: The clinical evaluation of ocular movements plays a crucial role in diagnosing and treating ocular motility disorders. This study introduces a novel deep learning-based image analysis technique for automatic measurement of ocular movements from photographs, aiming to explore the relationship between ocular movements and age.
Methods: A cohort of 207 healthy volunteers (414 eyes), spanning ages 5 to 60 years, participated in the study. Photographs were taken capturing cardinal gaze positions. Manual measurements of ocular movements were conducted using ImageJ with a modified limbus test, alongside automated measurements using our deep learning-based image analysis. Correlation analyses and Bland-Altman analyses were performed to evaluate agreement between manual and automated measurements. Additionally, generalized estimating equations were utilized to analyze the relationship between ocular movements and age.
Results: Intraclass correlation coefficients between manual and automated measurements for six extraocular muscles ranged from 0.802 to 0.848 ($P<0.001$), with biases ranging from -0.63 mm to 0.71 mm. Average measurements for superior rectus, inferior oblique, lateral rectus, medial rectus, inferior rectus, and superior oblique muscles were 8.62 ± 1.07 mm, 7.77 ± 1.24 mm, 6.99 ± 1.23 mm, 6.71 ± 1.22 mm, 6.81 ± 1.20 mm, and 6.63 ± 1.37 mm, respectively. Ocular movements in each cardinal gaze position exhibited a negative correlation with age ($P<0.05$).
Conclusions: The automated measurement approach utilizing deep learning demonstrates excellent agreement with manual measurements for ocular movements. This innovative method offers an objective means of assessing ocular movements, holding significant promise for enhancing the diagnosis and management of ocular motility disorders.

Introduction:

Accurate assessment of ocular movements is pivotal in diagnosing and managing ocular motility disorders, especially significant in cases of incomitant strabismus. Six cardinal positions of gaze have been identified, each primarily governed by one of the six extraocular muscles: adduction (mediated by the medial rectus [MR]), abduction (mediated by the lateral rectus [LR]), suprabduction (mediated by the superior rectus [SR]), supraduction (mediated by the inferior oblique [IO]), infraduction (mediated by the inferior rectus [IR]), and infraduction (mediated by

the superior oblique [SO]). Traditionally, clinicians rely on subjective qualitative scales to grade hyperfunction and hypofunction of extraocular muscles, leading to variability dependent on the clinician's experience. To address this variability, various quantitative methods, including kinetic (such as the limbus test and the lateral version light-reflex test) and static (such as the Hess and Lancaster screen) approaches, have been proposed, yet none have achieved gold standard status in the literature. Mai introduced a modified limbus test that measures maximal distances from the limbus to the eyelid margin at a 45-degree angle to the horizontal in suprabduction, supraduction, infraduction, and infraduction positions, providing an intuitive reflection of the function of vertical rectus and oblique muscles, thereby avoiding complex measurements and calculations of ocular movement angles, making it easily implementable in clinical practice.
Previous studies have endeavored to quantitatively measure ocular movements based on photographs capturing cardinal positions of gaze. However, these studies required manual measurement in photographic analysis, which still resulted in interobserver variability. Recognizing the advancements in deep learning with convolutional neural networks (CNN), which have demonstrated outstanding performance in automatic ophthalmological image segmentation, previous study analyzed morphological features of eyelids in normal participants based on photographs using CNN-based deep learning methods. This approach exhibited excellent reliability and reproducibility, indicating significant potential for automated evaluation of eyelid-related disorders. Expanding upon this application of deep learning in ocular motility disorders, we introduce a new technique for automatically measuring ocular movements using deep learning-based image analysis, in accordance with Mai's modified limbus test. Additionally, we explore the relationship between ocular movements and age in healthy volunteers.

Materials and Methods:

Study Participants:

A total of 207 healthy volunteers were recruited from the Department of Ophthalmology, Exclusion criteria included individuals with strabismus, eyelid diseases, orbital diseases, previous ocular or periocular surgery, history of neurological diseases, and age above 60 years old. Informed consent was obtained from all participants, and the study protocol adhered to the principles outlined

Photography:

Binocular movement testing was performed by a single experienced ophthalmologist to maintain consistency in assessment. Volunteers were instructed to track an object presented by the examiner through nine diagnostic positions of gaze, following standard clinical practices. Photographs were captured in these positions using a digital camera (Canon 1500 D, Canon Corporation, Japan) positioned 100 cm away at eye level. Verbal encouragement was provided to ensure head stability and maximal effort toward the extremes of gaze. For better observation during infraduction, upper eyelids were gently pulled, with the understanding that this manipulation would not impact measurements of inferior rectus (IR) and superior oblique (SO) muscles, which were referenced relative to the lower eyelids. A circular marker with a diameter of 10 mm was affixed to the volunteer's forehead as a distance reference.

Manual Photographic Measurement:

Following image collection, manual measurements were conducted using ImageJ (version 1.52; National Institutes of Health, Bethesda, USA) by another experienced ophthalmologist. Measurements were based on a grading system for extraocular muscles adapted from Mai, with each of the six cardinal positions of gaze corresponding to a specific extraocular muscle. Distances were measured from the medial canthus to the temporal limbus for the medial rectus (MR), from the medial canthus to the nasal limbus for the lateral rectus (LR), and maximal distances from the limbus to the eyelid margin at a 45-degree angle to the horizontal for the superior rectus (SR), inferior oblique (IO), inferior rectus (IR), and superior oblique (SO) muscles. Longer distances indicated lesser ocular movement. Accurate angle estimation was ensured through prior practice.

Automated Photographic Measurement:
Recurrent residual convolutional neural networks with attention gate connections based on U-Net (R2AU-Net) were utilized for eye location and segmentation. Training datasets comprised 30,000 facial images for eye location and 1862 facial images for eye segmentation. Testing datasets included facial images of 207 healthy volunteers in nine diagnostic positions of gaze. Random multi-scale boosting, elastic transformation, color perturbation, and random rotation were employed for pre-processing to enhance robustness. Measurements of extraocular muscles were automatically conducted based on masked images generated by the R2AU-Net framework. Pixel/millimeter ratios were calculated using adaptive threshold segmentation of the circular marker on the volunteer's forehead, enabling conversion of pixel measurements into millimeters.

Statistical Analyses:
Dice coefficients were used to evaluate the accuracy of automated eye segmentation tasks. Comparison between right and left extraocular muscle measurements obtained through automated and manual methods was performed using a T-test. Pearson's correlation coefficients and intra-class correlation coefficients (ICCs) were calculated to assess the strength of linear relationships and agreement between automated and manual measurements, respectively. Bland-Altman plots were used to visualize agreement. Generalized estimating equations were employed to evaluate the relationship between age and measurements of six extraocular muscles, adjusting for intraindividual data dependence. Statistical analyses were conducted using SPSS (version 23; IBM Corporation, Chicago, USA), with significance set at $P < 0.05$.

Results:
A total of 414 eyes from 207 normal participants, comprising 88 males (42.5%) and 119 females (57.5%), all of Asian ethnicity, were included in this study. The mean age was 23.2 ± 12.9 years, ranging from 5 to 60 years. Dice coefficients for automated eye segmentation tasks in the test set of 414 eyes were 0.947 for the eyelid and 0.952 for the cornea, respectively. The mean time for automated measurement per participant was 4.5 ± 0.3 seconds. T-tests indicated no significant difference between right and left extraocular muscle measurements obtained through automated and manual methods ($P > 0.05$), suggesting binocular movement symmetry among participants.
The mean ± standard deviation of automated and manual measurements for the six extraocular muscles are summarized in Table 1. Average measurements were 8.62 ± 1.07 mm for superior rectus (SR), 7.77 ± 1.24 mm for inferior oblique (IO), 6.99 ± 1.23 mm for lateral rectus (LR), 6.71 ± 1.22 mm for medial rectus (MR), 6.81 ± 1.20 mm for inferior rectus (IR), and 6.63 ± 1.37 mm for superior oblique (SO).
Pearson's correlation analyses indicated strong relationships between automated and manual measurements for all six extraocular muscles, with Pearson's r ranging from 0.881 to 0.957 (all P values < 0.001). Scatterplots depicting measurements from both methods . Intraclass correlation coefficients (ICCs) between automated and manual measurements ranged from 0.802 to 0.848 (all

P values < 0.001), demonstrating excellent agreement. Bland-Altman analyses revealed a bias of 0.64 mm between automated and manual measurements for SR, with 95% limits of agreement (LoA) ranging from -0.08 to 1.36 mm. Similar results were observed for the other extraocular muscles, with biases ranging from -0.63 mm to 0.71 mm and 95% LoA confirming agreement between methods

Generalized estimating equations indicated significant negative correlations between age and measurements of MR ($b = -0.012$, $P < 0.05$) and LR ($b = -0.013$, $P < 0.05$), and significant positive correlations between age and measurements of SR ($b = 0.010$, $P < 0.05$), IO ($b = 0.039$, $P < 0.001$), IR ($b = 0.013$, $P < 0.05$), and SO ($b = 0.019$, $P < 0.01$), suggesting decreased ocular movements in the six cardinal positions of gaze with aging.

Table 1. Automated and Manual Measurements of Six Extraocular Muscles and Their Correlation Coefficients

Measurements	Automated, mm (Mean ± SD)	Manual, mm (Mean ± SD)	Pearson's r	ICC
Superior rectus	8.94 ± 1.08	8.30 ± 1.09	0.943	0.804
Inferior oblique	8.11 ± 1.29	7.44 ± 1.23	0.946	0.828
Lateral rectus	6.68 ± 1.26	7.31 ± 1.25	0.920	0.817
Medial rectus	6.46 ± 1.25	6.95 ± 1.26	0.881	0.821
Inferior rectus	7.16 ± 1.23	6.45 ± 1.20	0.938	0.802
Superior oblique	6.98 ± 1.40	6.28 ± 1.36	0.957	0.848

*ICC = Intraclass Correlation Coefficients. ***$P < 0.001$.*

Discussion:

In this study, we introduced a novel deep learning-based image analysis approach to automatically measure ocular movements using photographs captured in cardinal positions of gaze. Our findings demonstrate excellent agreement between automated and manual measurements of six extraocular muscles. Additionally, we established normative values of ocular movements in these positions and identified a negative relationship between ocular movements and age.

Accurate and consistent evaluation of ocular movements is crucial, particularly in assessing treatment efficacy across different clinician visits. Traditionally, subjective grading scales have been employed, leading to standardization errors and limited quantification. While methods like the limbus test proposed by Kenstenbaum offer convenience, they still rely heavily on clinician experience and suffer from a learning curve effect. Moreover, existing quantification techniques, such as manual perimeters or costly devices like the scleral search coil, are either time-consuming, expensive, or limited in scope.

Photography, on the other hand, presents several advantages, including ease of acquisition, minimal patient effort, and objective assessment capabilities. Previous approaches have attempted manual evaluations based on photographs, but these methods are often time-consuming and prone to interobserver variability. Our modified limbus test, aided by deep learning-based analysis, simplifies ocular movement measurement by providing direct measurements from individual images, thus overcoming the limitations of manual methods.

The use of R2AU-Net in our study significantly enhances the accuracy and efficiency of eye segmentation tasks compared to traditional methods. This advanced neural network architecture integrates contextual information and improves representation ability, ensuring rapid and accurate measurements within seconds without the need for manual intervention.

Our study revealed a significant negative correlation between age and ocular movements, aligning with previous reports of age-related declines in motility. This finding has important implications for evaluating elderly patients with suspected extraocular muscle palsy, as subtle symmetric hypofunction may represent a normal aging phenomenon. Further neurobiological investigations are warranted to elucidate the mechanisms underlying age-related changes in ocular movements.

Several limitations of our study should be acknowledged. Firstly, participants with eyelid diseases were excluded, potentially limiting the generalizability of our findings. Additionally, eyeball size effects were not accounted for, and the study population was limited to individuals under 60 years old to avoid confounding factors related to aging. Moreover, our deep learning method has yet to be validated in populations with ocular motility disorders or other ethnic groups.

Despite these limitations, our study highlights the potential of automated ocular movement measurement in clinical practice. By providing rapid, objective, and reproducible assessments using only photographs, this technique offers valuable assistance in diagnosing and managing ocular motility disorders. Its simplicity and suitability for telemedicine make it a promising tool for widespread clinical application.

In conclusion, our study presents a novel image analysis technique for automated ocular movement measurement in healthy volunteers and identifies age-related changes in ocular movements. While further validation and refinement are needed, this approach holds great promise for enhancing the diagnosis and management of ocular motility disorders in clinical settings.

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