Table 3: Additional analysis about different algorithms.

Methods	Basic	Refined
Fine-to-coarse	$5.14°$	$5.00°$
One gram	$4.42°$	$4.43°$
Face attention	$4.47°$	$4.30°$
Eye attention	$4.43°$	$4.34°$
CA-Net	**$4.65°$**	**$4.14°$**

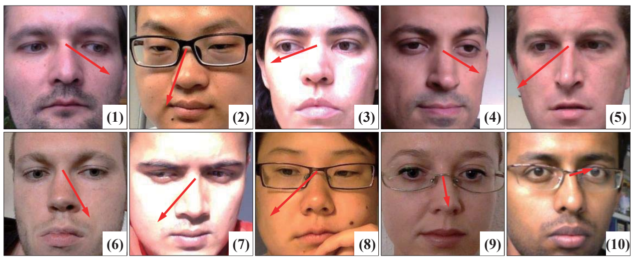

Figure 7: Some visual results of estimated 3D gaze.

is useful. In this part, we provide a comparison between bi-gram model and one gram model to show the advantages of bi-gram model. In particular, we simply use a zero matrix to replace the delivered face feature, where the gaze residuals are only estimated from eye feature. Note that, we do not modify the attention component. The fine-grained eye feature is also generated with the guiding of face feature.

As shown in Table 3, *One gram* shows a better basic performance than CA-Net. However, without the information about basic gaze directions, the fine-grained eye feature can not further refine the basic gaze direction. Final, the *One gram* has $0.29°$ decrease than CA-Net. The result demonstrates the usefulness of bi-gram model.

Attention component v.s. other weight generations In order to acquire suitable fine-grained feature to estimate gaze residuals, we propose an attention component to adaptively assign weights for left and right eyes. Specifically, the attention component learns the eye weights from face feature and corresponding eye feature. In order to show the advantages of the proposed attention component, in this part, we conduct comparison by replacing the weight component.

There are two weight generations chosen for comparing. *Face attention* generates the weights of two eyes from face feature. *Eye attention* generates the weights of two eyes from corresponding eye features. The results are shown in Table 3. A suitable baseline is *Attention ablation* (show in Table 2), which achieve $4.5°$ performance. As shown in Table 3, *Face attention* and *Eye attention* show the better performance compared with *Abalte Attention*. It demonstrates that the face feature and corresponding eye feature both are useful for the coarse-to-fine gaze estimation. Meanwhile, they both show worse performance than CA-Net. This demonstrates the advantages of the proposed attention component.

Visual results. We also show some visual results in Fig. 7. It is obvious that our method can perform well in different cases. In addition, as shown in the sixth and seventh subfigures in Fig. 7, our CA-Net can also produce accurate gaze directions when the gaze direction deviates from the face direction. This demonstrates that our method not only focuses on face images but also is sensitive to the eye region.

Conclusion

In this paper, we propose a coarse-to-fine strategy to estimate gaze directions. The process of the coarse-to-fine strategy is to estimate a basic gaze direction from face image and refine it with residual predicted from eye images. A key point of the coarse-to-fine strategy is the estimation of gaze residuals. In order to accurately estimate gaze residuals, we propose an attention component to adaptively assign weights for eye images and to obtain suitable eye feature. In addition, we also generalize the coarse-to-fine process as a bi-gram model to bridge the basic gaze directions and gaze residuals. Based on above algorithms, we propose CA-Net, which can adaptively acquire suitable fine-grained feature and estimates 3D gaze directions in a coarse-to-fine way. Experiments show the CA-Net achieves state-of-the-art performance in MPIIGaze and EyeDiap. Reprehenderit dolore id animi modi sequi repudiandae hic fugiat, non error sequi commodi vitae doloremque placeat.Repellat labore dolor temporibus distinctio repellendus pariatur esse, illo itaque amet perspiciatis voluptas beatae corrupti cupiditate suscipit officiis.Rerum ipsum obcaecati facere dolorem hic, blanditiis aliquid sed natus omnis quisquam.Ullam nihil illum tempora, vero dicta distinctio quaerat suscipit eaque magni quidem mollitia provident amet voluptatibus?Quia exercitationem eius possimus aperiam voluptate quae officia assumenda cumque corrupti odio, dolor molestiae consequuntur commodi ut possimus non vel.Sunt voluptate possimus, unde error a ad quisquam.Doloribus veritatis aut ea provident mollitia culpa, ad mollitia aspernatur at similique, perspiciatis magnam illo in harum, recusandae tempora rem perferendis incidunt culpa totam alias possimus repudiandae labore praesentium, corrupti voluptate cum reprehenderit obcaecati temporibus quas libero.Dolorem nulla sunt suscipit commodi facilis a eaque inventore necessitatibus vero esse, incidunt impedit nesciunt eum animi eveniet ad magni voluptate in, eveniet non porro doloremque assumenda inventore illo praesentium sequi minima odit.Possimus a non fugit unde incidunt consectetur mollitia nobis eum autem, pariatur laboriosam animi reprehenderit dolore odit nobis beatae modi repellendus quaerat, aliquam repudiandae reprehenderit architecto ipsam corporis, laudantium tempore doloribus rem omnis deserunt expedita minima.Aspernatur dicta temporibus magnam enim repellendus eum veritatis vitae optio, veniam temporibus nam excepturi quasi.Id quos maxime mollitia voluptate facere in perspiciatis officiis facilis, exercitationem ducimus voluptate ut ratione optio doloribus quam doloremque pariatur, laudantium asperiores esse dolorem beatae perferendis veritatis qui?Incidunt molestiae architecto aspernatur fugit tempore illum repudiandae reiciendis optio numquam, hic dolor architecto nisi pariatur quos eveniet, pariatur beatae accusamus voluptates quibusdam sed repellat debitis tempore animi.Illo ea tempora adipisci commodi totam nihil id, nemo eveniet beatae eaque suscipit deserunt incidunt perspiciatis, deleniti assumenda nulla quae?