Table2 enlists the mean error and standard deviation for color histogram (M1) and joint color-texture histogram (M2) methods.

Table 2: Target localization accuracies (mean error and standard deviation) by two methods on the sliding ball video

	Method	*Color histogram(M1)*	*Joint color texture Histogram(M2)*
1	Mean error	3.6	2.6
2	Standard deviation	5.7	5.6

Input of target model is sliding ball video file in .avi format. The output of target model is observed on MATLAB R2013a software. The target object sliding ball, which is to be tracked on the ground. Joint color-texture histogram method (M2) tracks the sliding ball more accurately than only color histogram (M1). Joint color-texture histogram is better than only color histogram. M2 has much better localization result than M1.

5. Conclusion

Object tracking is done by using features of target object. Feature extraction color and texture features of the target object are used. Combination of both color feature and texture feature is enhancing feature extraction quality. For features extraction LBP technique is used. Color aberration is caused by changing light and similar color to the background color. It affects on accurate location of target object. Both color and texture features are extracted by LBP technique. Joint color and LBP texture are used to reduce the computational complexity.

Experimental results indicate that joint color-texture methode (M2) performs much better than original color histogram methode (M1) with fewer iteration numbers. A simulation result shows that accuracy of joint color-texture histogram (M2) is better than only color histogram (M1) methode. It shows that joint color-texture histogram (M1) outperforms compared to color histogram (M1).This method is improved greatly the tracking accuracy with fewer mean shift iterations than standard mean shift tracking.

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