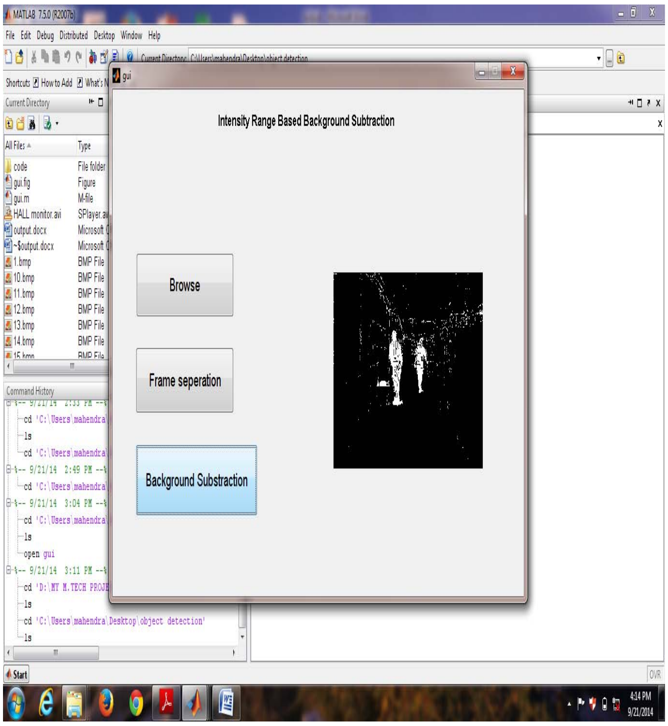

Figure: 2 Output Background Subtraction video

Such PCC increase or decrease in intensity may be caused by switching on or off of additional light sources, movement of clouds in the sky etc. Moreover, shadow having low intensity value when its intensity falls on any surface, decreases by some factor. There- fore, LIBS has an advantage of removing the shadows if any, at the time of detecting the objects. It may be noted that LIBS scheme is devoid of any assumptions regarding the frame rate, color space, and scene content.

5. Conclusion

In this work we have proposed a simple but robust scheme of background modeling and local threshold based object detection. Videos with variant illumination background, textured background, and low motion background are considered for simulation to test the generalized behavior of the scheme. Recent schemes are compared with the proposed scheme, both qualitatively and quantitatively. In general, it is observed that the suggested scheme outperfo rms others and detects objects in all possible scenarios considered. Background subtraction (BGS) is a widely used real time method for identifying foreground objects in a video stream. It is the first significant step in many computer vision applications, including human computer interaction, traffic monitoring, and video surveillance. This has prompted the development of a wide range of different BGS algorithms, along with a number of post processing techniques that aim to improve their performance. The most common paradigm for performing BGS is to build an

explicit model of the background. Foreground objects are then detected by calculating the difference between the current frame and this background model. Numerous computer vision applications depend on BGS to identify foreground objects. We have performed a comparative evaluation of BGS algorithms. This evaluation indicates that how the background is modeled does Influence performance. However, it also reveals that simple Modeling techniques.

6. Future Scope

As computers improve and parallel architectures are investigated, this algorithm can be run faster, on larger images, and using a larger number of Gaussians in the mixture model. All of these factors will increase performance. A full covariance matrix would further improve performance. Adding prediction to each Gaussian(e.g. the Kalman filter approach), may also lead to more robust tracking of lighting changes.Feature-based tracking algorithms perform recognition and tracking of objects by extracting elements, clustering them into higher level features and then matching the features between images

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