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# Motion Component Analysis of a Squat Reinforced Concrete Shear Wall

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ABSTRACT: Image processing techniques are used to understand the local specimen behavior in tests of large-scale civil structures. One such technique is Digital Image Correlation (DIC), which monitors the motion of a speckle pattern on the surface of a specimen. This paper introduces the Motion Component Analysis (MCA) method, which is based on (a) a principal component analysis decomposition of image appearance variations, and (b) a conversion of those appearance variations into motion patterns. MCA will be demonstrated using images from a hybrid simulation test of the seismic response of a squat reinforced concrete shear wall. Results from the MCA analysis and a comparison to DIC results will be shown.

KEYWORDS: image analysis; principal component analysis; digital image correlation; shear wall.

## 1. Introduction

Traditional displacement potentiometers and strain gages can measure global specimen behavior in large-scale tests of civil specimens, but they cannot adequately capture detailed information about local phenomena such as crack locations and crack widths. Researchers are increasingly using image processing techniques to gain insight into local specimen behavior.

By applying a random speckle pattern to the surface of a specimen, Digital Image Correlation (DIC) can monitor the motion of the pattern in a sequence of images and distinguish local behavior. DIC has been commonly used for small-scale mechanical device and biomechanics applications, but has only recently been extended to large civil structures (1). This paper introduces an alternative method, Motion Component Analysis (MCA). MCA is the extension of recent work (2; 3) that views scenes with repeated (though not necessarily periodic or exactly repeated) variations, and seeks to use the redundancy in the data to push the boundaries of detecting small motions. This paper is the first exploration of how to adapt and use the method from (2) with civil structures.

The advantage of the MCA-based method is that it simultaneously solves for the (arbitrarily shaped) regions of correlated motion and the motions within those regions. The method is based on (a) a principal component analysis (PCA) decomposition of the image appearance variations, and (b) a conversion of those appearance variations into motion patterns across the wall. Because MCA solves for motions based on large regions of temporally correlated changes, it allows sensitivity to very small motion magnitudes.

The implementation details of MCA will be described by processing images from a hybrid simulation test of a large-scale reinforced concrete squat shear wall exposed to an Operational Basis Earthquake (OBE) level ground motion excitation. A summary of the experimental design of the wall test and details about the wall photography are provided in the next subsections. Then the MCA method will be discussed, and results from the MCA analysis will be provided, with comparison to a DIC analysis.

### 1.1 Experimental Design

The hybrid simulation test of the seismic response of the wall was performed at the *nees@Berkeley* Laboratory at the University of California, Berkeley. The wall was 3 m (10 ft) long and 1.6 m (5 ft, 4-1/8 in) tall to the height of the actuator axis (aspect ratio 0.53). The actuator was located on the right side of the wall, and a steel plate, visible along the upper part of the wall in Figure 2, was used to distribute the load from the actuator across the top of the wall. Further details about the wall test can be found in (4). During the initial OBE motion, which is the focus of this paper, the wall developed minor shear-induced cracking at about a 45 degree angle, distributed throughout the wall web.

### 1.2 Wall Photographs

The concrete surface of the wall was painted with a flat white paint and then a random speckle pattern was drawn with a Sharpie marker. A 21 megapixel Canon 5D mark II with a Canon 24-70mm f/2.8L lens captured images of the random pattern throughout the experiment. The base camera sensitivity (ISO 100) was used to minimize the sensor noise and the aperture was adjusted to f/9. These camera settings require the use of powerful light sources. Each of three Elinchrom 1200W AC powered flashes was equipped with either a softbox or a shoot-through umbrella to provide a soft and even light. The shutter speed of the camera was set to its maximum sync speed, so the image contribution from continuous light sources that might be variable (daylight through windows, ceiling lamps etc.) were negligible relative to the contribution of the flash.

### 1.3 Contributions

The contributions of this paper include:

1. The derivation of a approach to visualize measurements of local phenomena in large-scale tests of civil structures.

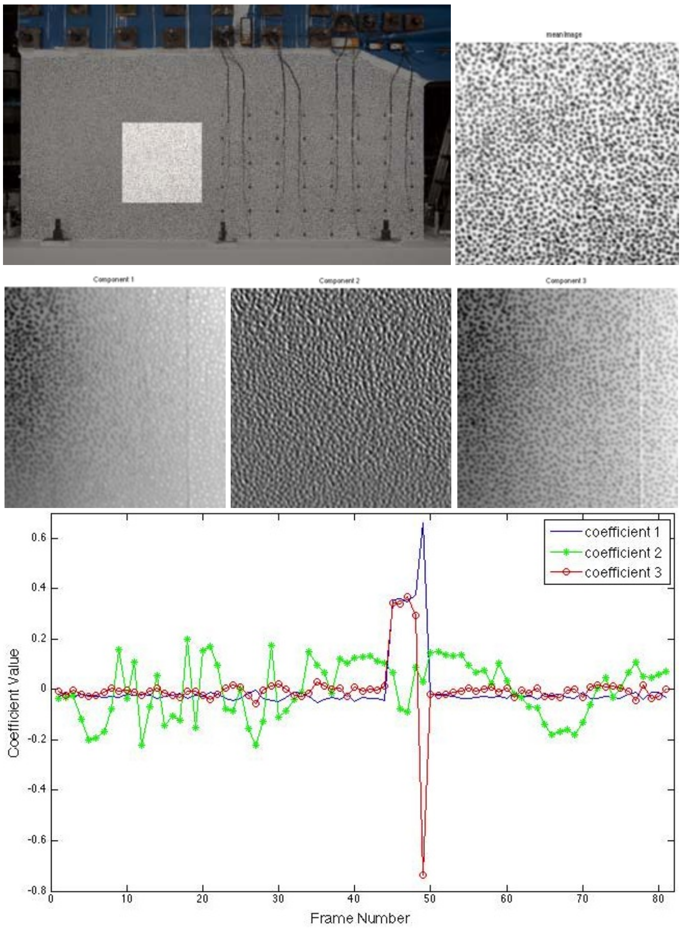


Fig. 1. From top to bottom, this shows the ROI of the wall used for this explanation, then the mean image, then the first, second, third basis images from the PCA decomposition. The bottom row shows the coefficients through time.

2. Exposition of the approach with image data from a large-scale test of a reinforced concrete squat shear wall.
3. A comparison of the sensitivity of the MCA approach to DIC methods.

We will also publicly share code for MCA analysis as well as simulation data suitable for testing this approach.

## 2. Motion Component Analysis

Images that capture the motion of civil structures responding to a load pattern are highly correlated. PCA is one way to automatically capture the ways that elements of a data set are correlated. When applied to a set of images $\{I_1, I_2, \ldots I_n\}$, PCA solves for the mean image $\mu$, a set of basis images $\{B_1, B_2, \ldots B_k\}$ and a set of coefficients $\{\vec{c}_1, \vec{c}_2, \ldots \vec{c}_n\}$. The coefficients for each time $c_t$ are $k$-element vectors that define how the basis images can be combined to approximate the image $I(t)$, as expressed in the following linear equation:

$$I(t) \approx \mu + \sum_i B_i \vec{c}_t(i)$$

For any fixed basis size $k$, the PCA decomposition is optimal in the sense that no other linear basis has a lower error (measured

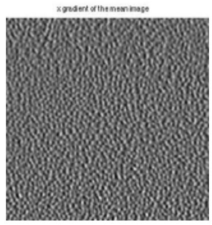


Fig. 2. The x-gradient of the mean image, which appears similar in form to PCA components that capture changes due to image motion.

by the sum of squared pixel differences) in approximating the set of images.

For images captured of the reinforced concrete squat shear wall during ground motion excitation sequences, this decomposition leads to very characteristic patterns. For a small part of the wall, Figure 2 shows a representative part of the scene, the mean image, and the first three PCA component images. These three component images capture the three most important variations in the image appearance. The final row shows the coefficient trajectory that defines how those components are combined to reconstruct each of the frames in the original video.

Components 1 and 3 are qualitatively different from component 2, and this is visible by inspecting both the component images themselves and the coefficient trajectory. Adding component 1 or 3 to the image would change that overall appearance of brightness of the scene, making the left side of that ROI brighter and the right side darker. This component captures lighting in the room that changed for a few frames before frame 60 (we believe that one of the flashes misfired), and otherwise the coefficients for these components are very close to zero.

Component 2 has a much more interesting coefficient trajectory, and a image component that is similar to the difference of the mean image and a shifted version of the mean image. To emphasize this point, in Figure 1 we show the x-gradient of the mean image. Adding the x-gradient to the mean image approximates the appearance change due to a one-pixel shift of the image, and adding component 2 to the mean image simulates some pattern of motion. The Motion Component Analysis (MCA) solves for the motion pattern (vector fields) that explains the PCA component.

The basis of differential motion estimation is the “Optical Flow Constraint Equation”. This starts with the assumption that all changes in the image are due to motion instead of, for example, the lighting getting brighter. It also assumes that the motion is small, so that over the distances that the scene may move from frame to frame, the intensity variation is linear.

Under these assumptions, the spatial intensity variation can be locally approximated by a Taylor Series so that for small values of $u$ and $v$:

$$I(x+u, y+v, t) = I(x,y,t) + \frac{\partial I(x,y,t)}{\partial x} u + \frac{\partial I(x,y,t)}{\partial y} v \qquad (1)$$

If the only image variation is due to motion of the scene, then there must be some image motion $u, v$ so that

$$I(x,y,t+1) = I(x+v, y+v)$$

Combining these equations, we get what is known as the Optical Flow Constraint Equation (5):

$$I(x,y,t+1) - I(x,y,t) = \\ I(x,y,t) + \frac{\partial I(x,y,t)}{\partial x} u + \frac{\partial I(x,y,t)}{\partial y} v - I(x,y,t).$$

The motion vector $u, v$ may be different at each pixel, and we can write $I(x,y,t+1) - I(x,y,t)$ as the temporal change $I_t$ at pixel $(x,y)$. Then, the above equation can be re-written in a form that is valid for all pixels:

$$I_t(x,y) = I_x(x,y)u(x,y) + I_y(x,y)v(x,y)$$

This relates the frame to frame intensity change $I_t$ to the motion $(u,v)$ and to the x and y-derivatives of the intensity $I_x, I_y$, each measured at the pixel location (x,y). This constraint is most often used to estimate scene motion by assuming that in a small neighborhood around (x,y) the motion $(u,v)$ is constant, and using all the $I_x, I_y$, and $I_t$ estimates in that region to solve for $u, v$. This creates a trade-off — if a larger region is used, there are more measurements, and therefore more robustness to noise, but if a smaller region is used, then the motion estimates can capture smaller scale motion variations.

For the case of motions that appear in squat shear wall failure, there are large regions of the wall that experience similar motions, separated by cracks in the concrete. If we can find these regions, then we can avoid this trade-off by integrating measurements across an entire region. While this seems like it might be a chicken-and-egg problem, because these regions are defined by their consistent motion, the PCA components have already captured patterns of consistent appearance change.

Those patterns are captured in the PCA component bases $B_i$. For components that are only due to image motion, then the correlated image (intensity) change $B_i(x,y)$ must be related to a motion vector field $u_i(x,y), v_i(x,y)$ such that:

$$B_i(x,y) = I_x(x,y)u_i(x,y) + I_y v_i(x,y) \quad (2)$$

This vector field $u_i(x,y), v_i(x,y)$ defines one motion component pattern. The next section gives formal implementation details of this method.

## 3. MCA METHOD

A program for performing the MCA decomposition is implemented in Matlab. The program allows the selection of an ROI in the image. For images from the ROI, the procedure includes the following steps, which are expanded upon below:

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**MCA algorithm**

1. Blur each image using a Gaussian blur kernel of size $\sigma$.
2. Compute the mean image and subtract it from all images.
3. Compute the PCA basis of the mean subtracted images.
4. Compute the motion vector field implied by each basis.

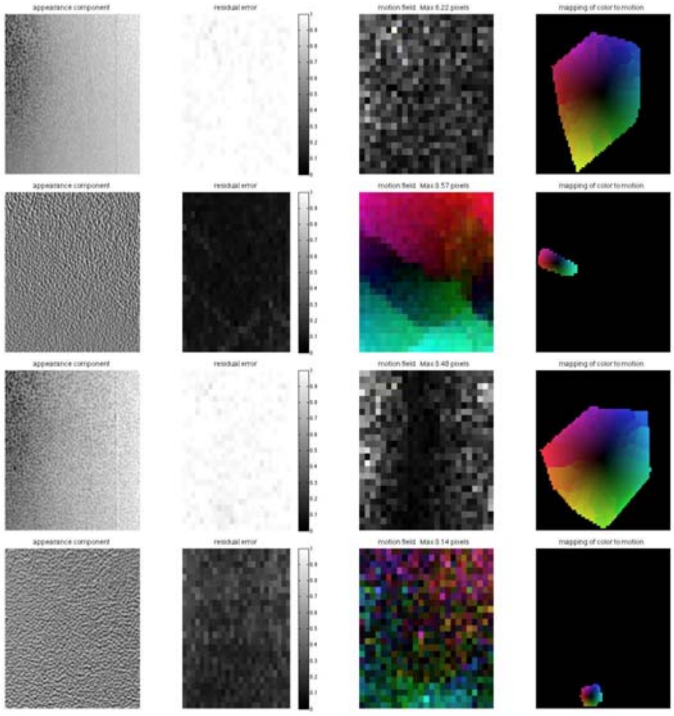

Fig. 3. Top to bottom shows the conversion of the first 4 PCA components for the ROI from Figure 2, and their conversion into motion components. For each component, we show, from left to right, the PCA component, then the residual error of interpreting this component as motion (values closer to 0 indicate lower error), then a color coded motion field of what this motion encodes, and then the mapping of color to motion. Here, the first and third components code for brightness changes, and the second and fourth code for motions. The second encodes variations in the horizontal motion of the wall, and the fourth component captures very very small vertical motions.

5. Evaluate whether each basis codes for motion or not.
6. Visualize the vector fields.

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Figure 3 illustrates the endpoints of steps 1, 3, 5 and 6.

Step 1 is important because of the Taylor series approximation that defines the relationship between motion and appearance change. To ensure that this relationship is approximately linear, the blurring kernel size should be about the size of the maximum motion (in pixels) in the scene.

Steps 4 has the goal of converting the components in Figure 1 into the motion field that would cause that type of image change. Equation 2 defines a constraint between an image basis and its motion field, but this gives one equation for the two unknowns at each pixel. Using a standard optic flow consistency check, we divide the image into small blocks and solve for a single $u, v$ vector using the constraint for all the pixels in that block.

Step 5 has the goal of distinguishing component 1 from component 2 in Figure 1. This is done by evaluating the residual of linear system solved in step 4. Components that relate to image motion have a residual near 0. Components that relate to lighting change are not consistent with any constant motion, and therefore, a very high error results from using a $u, v$ for all pixels

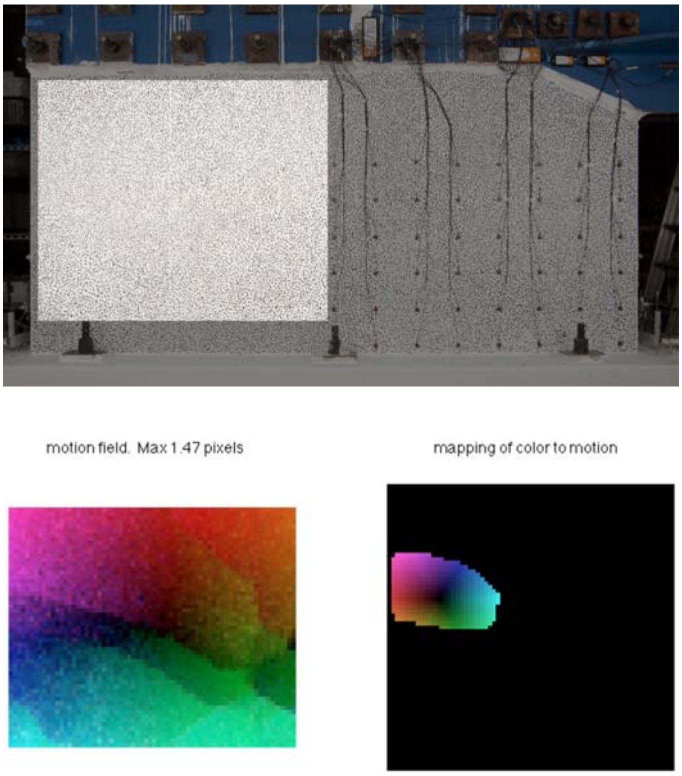


Fig. 4. Top shows the ROI selected from the test wall, and the bottom shows the MCA motion component.

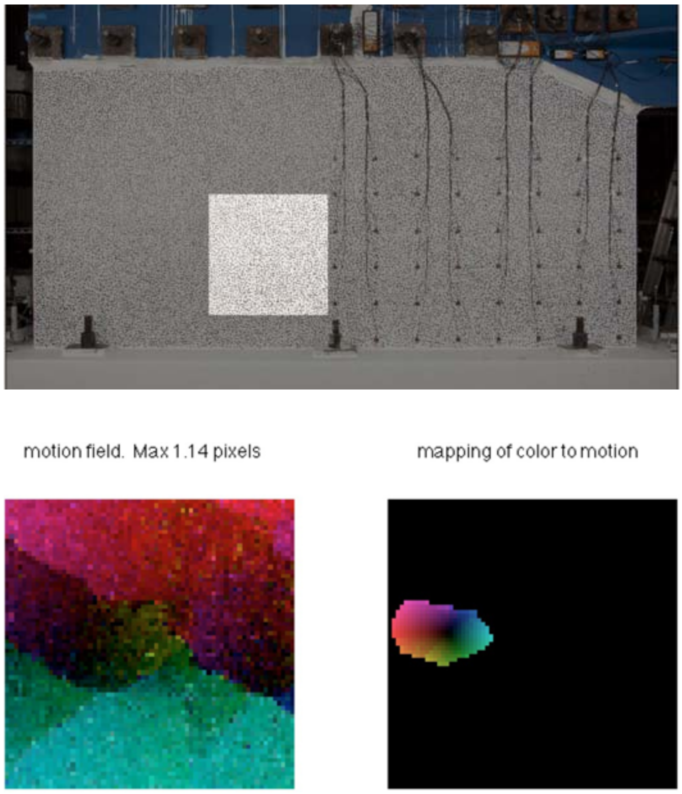


Fig. 5. Top shows the ROI selected from the test wall, and the bottom shows the MCA motion component.

in a block in Equation 2. The second column of Figure 3 shows this residual error and highlights that it clearly differentiates components that are and are not related to motion.

Step 6 visualizes the motion field as a color map. Because the motions of the wall were small and highly correlated, displaying the vector field as a set of arrows would be difficult to interpret. Instead the vector field is color coded, where the mapping of color to vector may differ for each component. The third column of Figure 3 is the color coded vector field and the final column is the mapping of color to motion vector.

## 4. Results

Applying MCA to images of a reinforced concrete squat shear wall gives a motion vector field of the dominant motion pattern of this wall during the OBE motion. The motion component and the mapping of colors to motion vectors is displayed in Figure 4. This motion field highlights crack locations as locations in the motion field where there is a rapid change in the motion vector, which leads to a boundary where one color (corresponding to a motion vector) differs from a neighbor on the far side of the crack.

Figure 5 shows the analysis repeated just on a smaller subset of the wall. Note that the color coding is different in the two plots, in each case the entire color space is used to emphasize relative motions in the ROI.

We compare the motion fields we compute with a frame to frame displacement map computed with DIC (6). The motion fields capture correlated motions visible in the scene over the entire image sequence. To compute the motion field between two specific images, we multiply the motion component by the difference of coefficients for those two frames. Figure 6 shows our motion fields and the DIC motion estimates. The x-component motion estimates are very similar and only differ slightly in the smoothness term applied within the estimates (our approach has no smoothing between motion blocks). The y-component motion has some discrepancy, but this is due to DIC comparing only two frames and MCA correlating motions over all images in the OBE ground motion.

## 5. Conclusions

Traditional measurement devices in large scale tests of civil specimens cannot adequately capture detailed information about local phenomena such as crack locations and crack widths. Image processing techniques are used to gain insight into local specimen behavior. This paper introduced the Motion Component Analysis (MCA) technique and applied it to a series of images from a hybrid simulation test of the seismic response of a squat reinforced concrete shear wall, exposed to a ground motion excitation.

MCA solves for regions of correlated motion and the motions within those regions. It is based on principal component analysis (PCA) decomposition of the image appearance variations and conversion of those appearance variations into motion patterns. The results from the MCA implementation, which computed correlated motions over the entire sequence of images, were compared to results from a frame to frame DIC analysis. The similarity between the MCA and DIC results verifies this technique for capturing local cracking behavior of the wall. Small discrepancies result from the difference between MCA

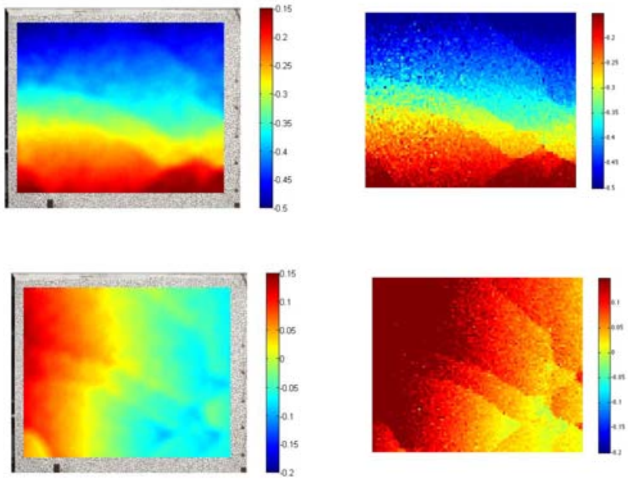

Fig. 6. A comparison between the DIC vector field computed between two frames, and the MCA estimate of the motion between those frames. Top left shows the DIC x-component motion estimate, and the top right shows the MCA x-component estimates. The bottom shows the y-components.

looking at the entire image set and DIC looking at comparing two distinct images. Future studies will include MCA analysis of larger ground motions that the wall experienced after the OBE motion, and further comparison to DIC.


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## REFERENCES


[1] Salmanpour, A. and N. Mojsilovic, "Application of digital image correlation for strain measurements of large masonry walls," in *Proceedings of the 5th Asia Pacific Congress On Computational Mechanics*, paper # 1128, Singapore, December 11-14, 2013.

[2] Michael Dixon, Austin Abrams, Nathan Jacobs, and Robert Pless, "On analyzing video with very small motions," in *IEEE Conference on Computer Vision and Pattern Recognition*, 2011.

[3] Hao-Yu Wu, Michael Rubinstein, Eugene Shih, John Guttag, Frédo Durand, and William T. Freeman, "Eulerian video magnification for revealing subtle changes in the world," *ACM Transactions on Graphics*, vol. 31, no. 4, 2012.

[4] Whyte, C. A. and B. Stojadinovic, "Effect of Ground Motion Sequence on Behavior of Reinforced Concrete Shear Walls in Hybrid Simulation," *ASCE Journal of Structural Engineering*, 2013. Posted online ahead of print.

[5] B K P Horn, *Robot Vision*, McGraw Hill, New York, 1986.

[6] Blaber, J., "Ncorr - 2D Digital Image Correlation Software, http://ncorr.com/download/ncorr_v1_1.zip," 2014.